EOCAP II PROJECT

Titled:
WETLANDS INFORMATION SERVICES
A COMMERCIAL APPLICATION OF REMOTE SENSING
AND GEOGRAPHIC INFORMATION SYSTEMS FOR
ECONOMIC DEVELOPMENT PLANNING
AND WETLANDS MANAGEMENT

Under

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Stennis Space Center, Mississippi

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By:

APPLIED ANALYSIS INC.
46 Manning Road, Suite 201
Billerica, Massachusetts 01821

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EXECUTIVE SUMMARY

The EOCAP II project greatly assisted the commercialization of a software product for remote sensing. It not only provided support and mechanisms to refine and introduce the product to the marketplace, but it also provided the opportunity for a thorough and documented demonstration and accuracy assessment of the product in two critical and high visibility market segments, wetlands and forestry management.

The United States Fish and Wildlife Service has estimated that over 200 million acres of wetlands existed in the contiguous United States in the late 1700's. By 1980 less than 100 million acres still remained, with an annual loss placed at over 450,000 acres per year. This fact when considered with the Administration's "no net loss of wetlands" position, make accurate, responsive, and simplified means to identify and map wetlands more critical.

The concept of using indicator species to classify an area as wetland has been used by ecologists intensively for the last decade. Because vegetation is considered a characteristic feature of wetlands, the federal government has compiled a national list of plant species for regions of the country that occur in wetlands. In the Southeastern part of the U.S., bald cypress and water/swamp tupelo are three of the most common wetland species indicating an obligate wetland (99% expected frequency in wetlands). In delineating and mapping wetlands, identifying the location of an obligate wetland is the first step. The next step is to identify the wetland/upland boundary around the wetland, which is a far more difficult task. This category of indicator species includes those that occur in the transition zone between wetland and upland.

This zone is where wetland species gradually intermix with the upland species and is characterized by complex species combinations and high spatial heterogeneity. The next zone, further removed from the obvious wetland, is called the upland zone.

For the demonstration, indicator species were selected for each of these zones: obvious wetlands in which the cypress and bald cypress were used; for the transition zone swamp chestnut oak, laurel oak, and water oak were used; and for the upland zone, the loblolly pine was used. As the project work evolved it became clear that the subpixel process could be used for a large variety of applications, which resulted in the incorporation of a Forestry application (upland species) using loblolly pine.

Applied Analysis Inc. (AAI) made a timely and unique breakthrough in the processing and extraction of remotely sensed information from LANDSAT TM (and other remotely sensed) multispectral data. This subpixel technique, called the Applied Analysis Spectral Analytical Process (AASAP) is an innovative addition to traditional multispectral classification tools. Subpixel classification detects objects that occupy only a small fraction of a pixel and discriminates between materials with subtle spectral differences. To supplement existing classification tools, AASAP subpixel classification software is an add-on module to ERDAS IMAGINE software. ERDAS, Inc., the industry leader, has made IMAGINE a powerful image processing and analysis software package that AASAP is seamlessly integrated with.

Each pixel in a scene typically contains a mixture of materials. These materials contribute to the pixel's characteristics. With AASAP, the contribution of specific materials of interest (MOI) within the mixed pixel are identified. Thus, enhanced discrimination and the ability to classify objects smaller than the spatial resolution of the sensor is achieved.

The primary components of AASAP consists of automated signature derivation and subpixel classification tools. Signature derivation creates customized spectral signatures that address specific MOI requirements. Subpixel classification reports the locations of pixels containing identified fractions of the MOI, or in other words, the amount of the specific tree species in each pixel. During classification a scene normalization algorithm (atmospheric correction) is applied, which corrects for atmospheric and sun angle effects. Scene normalization permits spectral signatures to be applied from scene-to-scene. This automated process allows for the detection of the specific indicator species to the subpixel level without any human analysis or photo-interpretations. The AASAP process makes maximum use of the existing ERDAS IMAGINE tools that users of traditional classifiers have been using for years. This allows an experienced ERDAS user to understand and use AASAP in less than one day.

A technical paper describing the AASAP classification of wetland and forestry tree species for the product demonstration was submitted for publication in Photogrammetric Engineering and Remote Sensing in May 1995. An overview of this application is presented here and is attached as Appendix C. The study area included five wetland study sites in southeast South Carolina and eastern Georgia. The study sites cover a broad geographical area (approximately 120 miles apart) and are typical representatives of inland wetlands in the flatlands coastal plain physiographic province ranging from Georgia to North Carolina. Each study site contains wetland and upland ecological zones and a broad transition zone between the two. Additionally, a forested site containing loblolly, longleaf, and slash pines was selected in the United States

Forest Service managed Savannah River Site in South Carolina. This forested site was to demonstrate the ability of the AASAP subpixel process to differentiate between similar types of pine species and to show another application using this subpixel technique.

The wetland indicator species and forested pine species may occur as a single isolated plant or tree. The ground area occupied by the indicator species may frequently be smaller than the ground area sampled by a remote sensor (ground sampled distance (GSD) or instantaneous field of view (IFOV) of the sensor). Subpixel image analysis techniques, such as AASAP, have the ability to detect spatially small occurrences of the indicator species. The ideal commercially available sensor for detecting these species in a broad area coverage mode was the LANDSAT Thematic Mapper (TM). The spectral band characteristics of the TM are suitable for detecting variations in vegetation, and the 30m x 30m GSD has proven, in other AASAP applications, to be suitable for detecting subpixel objects the size of individual tree crowns. The TM sensor is a space-borne sensor that is fully operational, provides repeatable coverage, and has wide commercial acceptance. For these reasons TM is used as the primary sensor for earth resource monitoring and was the sensor AAI choose for commercial use with AASAP. The LANDSAT TM collections were accomplished in May 1992 because the time and rate of Spring "leaf-out" is specie specific and maximum spectral contrast between many species occur at that time. At approximately the same time as the LANDSAT collection, a NASA aircraft collected CAMS imagery and color infrared (CIR) photography at a scale of 1:6,600 with a 9" format camera. CIR film is the ideal film for vegetation analysis.

Extensive field sampling was accomplished by Clemson University and USFS researchers. Use of the CIR photography, CAMS imagery, TM imagery, USGS 1:24,000 scale topographic images, National Wetland Inventory (NWI) maps 1:24,000 scale, digital Soil Conservation (CSC) soil survey sheets 1:20,000 scale, and site visits using hand-held GPS field instruments were used to located pixels to extract whole and subpixel signatures using the automated AASAP as well as to verify the detections after processing the TM scenes with the derived signatures. To ensure image geometric correction/accuracy, ground control points were required. Ground control points with referenced features were located accurately in both the imagery and in the field sites. The TM imagery was geometrically corrected and spatially registered in a Geographical Information System (GIS). The GIS served as a computerized system for storing and manipulating spatially registered planes of digital geographic data.

Random sampling techniques were used to independently determine the accuracy of the AASAP subpixel process. Field verifications were accomplished for 200 pixel locations for tupelo, 200 pixel locations for cypress, and 200 pixel locations for loblolly pine. The total accuracy assessment for tupelo was 91%, for cypress 89%, and for loblolly pine 88%. Of importance was that the accuracy of AASAP detections away from the training area (pixels not in the area of selected pixels to derive multispectral signatures of the species) was high compared to the performance of traditional classification techniques, which at times can drop to 50%.

The foremost objective of this work was to demonstrate the commercial vitality of AASAP, not only for wetland and forestry applications, but for a wide range of related applications and to provide a software product that could be easily used by thousands of ERDAS users. Additionally, during this three-year EOCAP II contract, AAI was able to participate in other governmental and IR&D efforts to further automate the process to enhance its acceptability for a wide range of potential users. The use of Product Evaluation Panels (PEP) during this three-year period was a major factor to cultivate potential markets and to receive valuable recommendations to provide a more viable product. Three PEP meetings were conducted, one at the University of South Carolina in Beaufort, South Carolina; one in Atlanta hosted by the USFS; and the third at Clemson University in Clemson, South Carolina. Among many valuable suggestions at the PEPs, the one to include the pixel fraction information (already available as a secondary output) as a major selling point, and to display this information as a regular report, was extremely worthwhile.

AAI researched the leading image processing and analysis packages available in the market and decided to integrate AASAP with the industry leader, ERDAS, Inc. of Atlanta, Georgia. ERDAS had sold over 7,000 licenses worldwide through 1994, and the projection was for healthy growth periods throughout the 1990s. AAI commenced negotiations with ERDAS for AASAP to be sold as third party software under ERDAS. This started out on a non-exclusive basis and changed to an exclusive arrangement, where only ERDAS and AAI can sell AASAP for a specified period of time under pre-determined sales formulas. Negotiations were concluded and AASAP would be sold as an add-on ERDAS module starting by the end of the second quarter of Calendar Year 1995. AASAP runs on Sun SPARC, HP 9000 Series, and SGI UNIX computer workstations. These workstations are the most widely used and account for over 90% of the ERDAS base. The process works with imagery for the two most widely used sensors, LANDSAT TM (six bands) and SPOT (three bands). The process is being enhanced to accept other multispectral imagery. AASAP has been ported to the latest ERDAS IMAGINE software, Version 8.2, and is backward compatible to Version 8.1. To ensure stable software would be provided to the potential customer, four beta sites were established and used for over nine months. AAI provided hands-on training and maintained close contact with each site. Clemson University has functioned as an alpha and beta site for over 15 months.

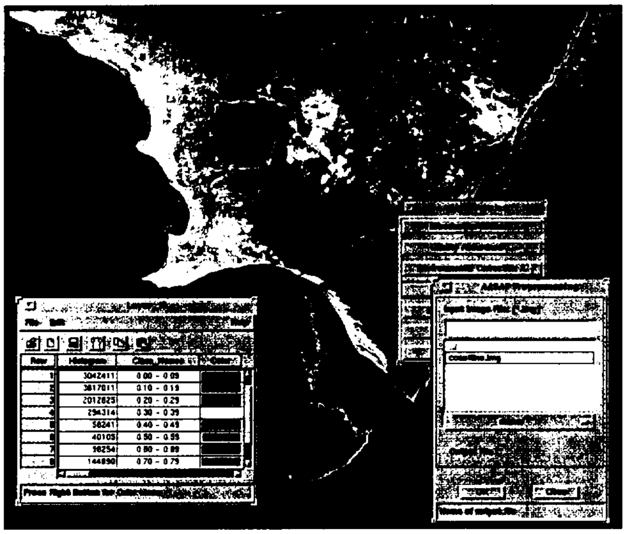
The kinds of applications in addition to wetlands and forestry include, agriculture, geology, terrain characterization, bathymetry (to include environmental/pollution), and point-type targets. The kinds of markets and customers run the full gamut from commercial, government, universities, and quasi-governmental/nonprofit organizations, which are currently being serviced by ERDAS.

The pricing for the product was initially set at $5,500 for the first license, which includes one year of software support. An introductory offer was established with a 25% price reduction for the first 90 days. Quantity discounts and government discounts are available consistent with ERDAS' standard pricing policy.

The initial penetration of the market will be through direct contact with selected segments of ERDAS' established base (primarily through the ERDAS worldwide sales/distribution force), advertisements in periodicals like <u>Earth Observation Magazine</u> and <u>Photogrammetric Engineering and Remote Sensing</u> (PE & RS), and direct mailings to PEP members and PEP-type contacts. AAI and ERDAS have produced marketing literature titled the AASAP Subpixel Product Fact Sheet and prepared articles for selected periodicals. The Product Fact Sheet is enclosed as Figure 1.

The User's Guide, which provides the step-by-step procedures on how to use AASAP, has been extensively alpha- and beta-site tested. The User's Guide also contains a complete Demo section

AASAP Subpixel Product Fact Sheet



Overview

The Applied Analysis Spectral Analytical Process (AASAP) subpixel processing technique is an innovative addition to traditional multispectral (MSI) classification tools. Subpixel classification detects objects that occupy only a small fraction of a pixel, and discriminates between materials with subtle spectral differences. To supplement existing MSI classification tools, AASAP subpixel classification software is a plug-in module to the ERDAS IMAGINE software.

Each pixel in a scene typically contains a mixture of materials. These materials contribute to the pixel's characteristics. With AASAP, the contribution of specific materials of interest (MOI) within the mixed pixel are identified. Thus enhanced discrimination and the ability to classify objects smaller than the spatial resolution of the sensor is achieved.

The primary components of AASAP consist of automated signature derivation and subpixel classification tools. Signature derivation creates customized spectral signatures that address specific MOI requirements. Subpixel classification reports the locations of pixels containing identified fractions of the MOI. During classification, a scene normalization algorithm is applied, which precisely characterizes atmospheric and sun-angle effects. Scene normalization permits spectral signatures to be applied scene-to-scene.

Benefits of Subpixel Processing

AASAP subpixel processing provides the following advantages for multispectral MOI characterization and detection:

- Materials containing as little as 20% of the measured radiance of a pixel can be detected
- For each pixel classified, the pixel fraction occupied by the MOI is reported
- Pixels can be classified with higher levels of discrimination, such as species of trees or types of crop
- Signatures from one scene can be used for classification in other scenes
- Consistent classification within and outside the training area
- Improved classification accuracy

The Subpixel Processing Technique

The AASAP subpixel processing technique is a new approach to both deriving spectral signatures and applying them to imagery. Traditional classification techniques develop signatures by combining the spectra of training set pixels. These signatures encompass the contributions of all the materials in the training set. In contrast, AASAP signature derivation extracts a component of the pixel spectra that is most common to the training set. This results in a signature that is representative of a specific material or set of materials.

Upon deriving a signature, conventional classifiers identify pixels in the scene that have the same spectral properties as the signature. AASAP, however, locates pixels containing the signature as a fractional component of the overall pixel spectrum. A subpixel background estimation and removal process is performed by AASAP to produce a residual spectrum for each pixel in the scene. A detection occurs when the difference between the residual spectrum and the signature falls within a set of tolerances. Suppression of subpixel background materials in AASAP allows classifications of MOIs, even when they occur in "mixed pixels" containing a wide range of background materials. AASAP reports the amount of MOI associated with each pixel as both a histogram and graphic overlay.

How to Use the Product

AASAP was designed as an additional classifier to supplement your existing suite of classification tools. It provides a higher level of discrimination for most of your applications. AASAP is highly specific in that the background removal function attempts to discard materials from pixels with the intent to provide a discriminating and unique signature of the MOI. The resulting signature is specialized to your problem or MOI. A good way to think about the difference between AASAP signature derivation and traditional methods is that AASAP attempts to exclude dissimilar materials in pixels, while the traditional methods attempt to include all materials in the pixels. In some applications, an operator would use one of the conventional classifiers to classify a larger area that contains a mixture of materials. In other applications, a more precise classification of the same area, such as tree species, requires the use of AASAP's subpixel classifier.

To derive a whole pixel or subpixel signature of the MOI, you may choose to use any of the existing ERDAS IMAGINE Area of Interest (AOI) tools to develop your training set. The result will be subpixel detections with the use of either a whole or subpixel signature. AASAP takes full advantage of ERDAS IMAGINE display, analysis, and reporting tools.

Data Types Supported by AASAP

AASAP subpixel classification may be applied to Landsat TM and SPOT HRV data. Support of additional MS data types is planned for the future.

Hardware Platforms

AASAP runs on Sun SPARC, HP 9000 series, and SGI UNIX workstations.

Applied Analysis Inc.

The AASAP subpixel classification technique is phenomenologically driven and was developed by world class phenomenology scientists at Applied Analysis Inc. AAI has devoted over ten years to provide methods to solve the mixed pixel problem. The product has been automated to permit widespread use of this powerful classification technique.

Applied Analysis Inc.
46 Manning Road, Suite 201 • Billerica, MA 01821-3976
508-663-6828 • 508-663-6389

(including imagery), where the customer can derive signatures and run classification and then compare their results to the AAI results. To assist the customer in evaluating their performance with the demo, high resolution ground truth air photos were scanned in and are available on their screen. The user can complete the demo of AASAP using all the functions in less than 30 minutes.

In conclusion, the EOCAP II project provided the opportunity for a thorough and documented accuracy assessment of the AASAP subpixel process as well as the support and mechanisms to refine and introduce the product into the commercial marketplace. It is anticipated that sales and delivery of the product should start during late summer 1995.

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1.0 INTRODUCTION:

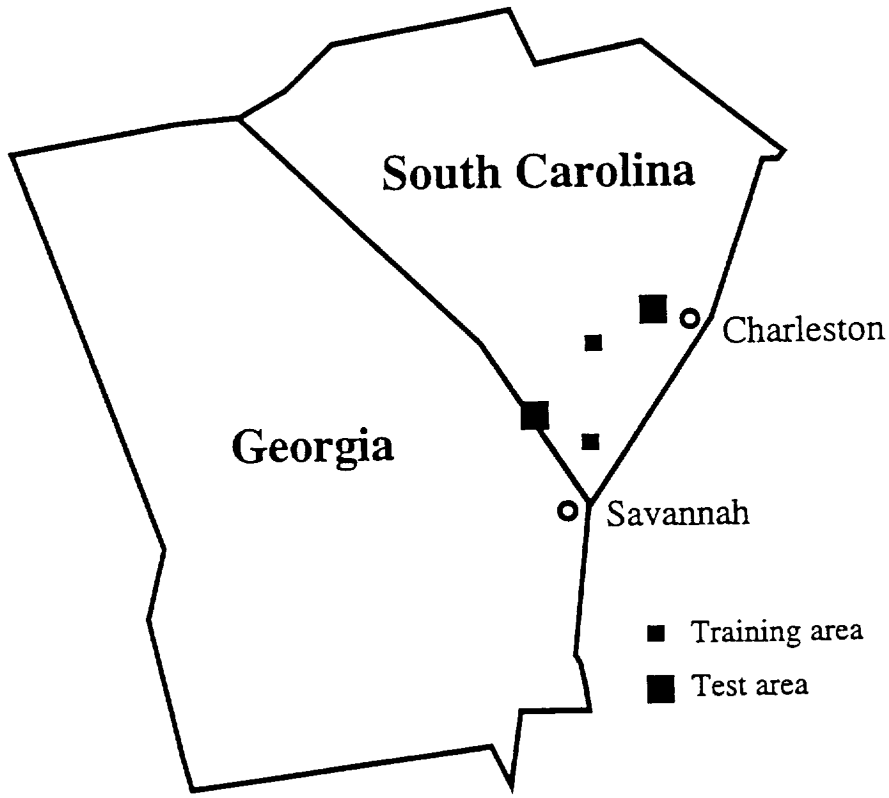
This EOCAP II project is a remote sensing effort that makes use of commercially available remote sensing imagery, commercially available UNIX computer workstations, commercially available image processing and analysis software, and integrates them with the Applied Analysis Inc. (AAI) unique and innovative technique, a subpixel process called the Applied Analysis Spectral Analytical Process (AASAP), to significantly improve the discrimination of materials. AASAP solves the mixed pixel problem by detecting the components of pixels, thereby improving the discrimination and accuracy of information extracted from available imagery. Currently, traditional classifiers search for the common or similar spectral properties, and as such, groups materials into a limited number of classes. This usually forces different types of materials into one class or another. The AASAP subpixel process searches for the components within a pixel and excludes different types of materials resulting in a finer level of discrimination with more accurate material classifications. The technical approach AAI pursued was to remove the background material and the resultant components in the pixel would represent the material of interest. AAI's EOCAP task was to package and market this new technology in a way that it could be easily understood and used by a large segment of the remote sensing community.

1.1 Project Description.

The project started out as a commercialized application of Remote Sensing and Geographic Information Systems for economic development planning for Wetlands Management. About half-way into the project it was realized that the subpixel process had very broad applications, and that an additional application should be undertaken to demonstrate the breadth and increased value of the product. The additional application was in the forestry area, however, the same procedure and methods were used for both applications and they could be used for a large variety of other applications.

A demonstration of the product, including documentation of accuracy, was considered central to the strategy for selling the product. A technical paper describing the AASAP classification of the wetland and forestry tree species for the product demonstration was submitted for publication in Photogrammetric Engineering and Remote Sensing in May 1995. An overview of this application is presented here and is attached as Appendix C. The study areas for the demonstration were in South Carolina and Georgia on forested wetlands and in the Savannah River Site in South Carolina for the forest application. LANDSAT TM imagery was collected on May 4, 1992 after complete spring leaf-out. Four study areas from within the wetlands LANDSAT TM scene were analyzed (Ref. Figure 2), and a larger study area in another LANDSAT TM scene acquired in May 1991 was used for the forest application. The wetland areas were processed with AASAP to detect the location of cypress and tupelo trees, and the forestry area was processed to detect loblolly pine trees and to discriminate between longleaf and slash pine. Ground truth data was obtained from the field, the NASA CAMS imagery, CIR photographs at 1:7,000 resolution, and the National Aerial Photography Program (NAPP) CIR aerial photographs (1:40,000 scale). This data was used to assist in locating signature derivation training sets and to accomplish the accuracy assessment.

Figure 2



South Carolina
Georgia
Charleston
Savannah
Training area
Test area

Spectral signatures were developed for the wetland species and forestry specie and applied to the entire scene. Clemson University and the U.S. Forest Service (at Clemson University) accomplished the accuracy assessment with field measurements of the different species. A field verified accuracy of 90% was achieved considering errors of omission and commission. Outside the training area the accuracy was only about five percent less, and this compared very favorably to traditional classification techniques where the classification performance outside the training area dropped sharply.

Concurrently with the study site work, AAI was preparing the product for the commercial market. Initially, the early market analysis considered a software product and a service bureau type of operation. As the project progressed, there were certain outside developments that resulted in the service bureau option being dropped. A major influence was the vast improvement in workstation performance (speed and storage) with substantial decreases in pricing. The second major influence was the ability of AAI to automate (through another contract) the signature extraction and environmental correction factor so that an ERDAS user would be able to derive their own signatures. This meant that an AAI scientist was not needed to assist in the development of multispectral signatures. These two major developments caused AAI to re-assess the need and viability for AAI to extract and sell signatures through a service bureau type operation. About half-way into the project AAI described the changing nature of the market conditions to NASA EOCAP and AAI pursued a focussed and vigorous effort to reach this broader market through an easy-to-use add-on module integrated with ERDAS IMAGINE. AAI was involved in negotiating a third party software arrangement with ERDAS, Inc. of Atlanta, Georgia. By the end of 1994, ERDAS has an installed user base of 7,000 licenses with sales increasing at about 15%-20% per year. The third party software arrangement changed from a non-exclusive to an exclusive with only ERDAS and AAI marketing and selling the AASAP software product. This meant that AASAP would be marketed and sold through the industry leader with a worldwide sales force and distribution network already in place. The remote sensing market for AASAP was now defined as the largest available with the established presence of ERDAS throughout the world.

AAI used the Product Evaluation Panel (PEP) approach to introduce the remote sensing community to the methodology and benefit of subpixel analysis. AAI also received valuable feedback from commercial, government, and university users within the PEP. Three PEP meetings were held at different locations in the Southeastern part of the United States with experienced image processing and analysis users. This technique was used to prime the market and provide the stimulus for future sales.

To ensure that the software was stable, alpha and beta testing sites were established. The software started testing outside of AAI at the Clemson University alpha site in April 1994 and at four other beta sites in October 1994. The four beta sites were Clemson University, ERDAS, Naval Space Command, and Air Force Space Command. The beta sites were selected to represent university, commercial, and government customers. AAI provided three days of formal training to each alpha/beta site participant, and over the course of more than one year, numerous valuable suggestions were received and incorporated into the product.

The AASAP software product was offered for sale in June 1995 initially by AAI, to be followed later in the summer by ERDAS.

1.2 Objectives.

The overall objective was to develop a commercial product using remote sensing technologies for applications requiring subpixel techniques called the Applied Analysis Spectral Analytical Process (AASAP).

1.2.1 The detailed objectives that support the overall objective are as follows:

(a) Determine indicator species locations to predict the presence of wetlands for the demonstration product.

(b) Determine the ability to discriminate between similar tree species, like loblolly, slash, and longleaf pine for the demonstration product.

(c) Provide a detailed, credible accuracy assessment of AASAP for the demonstration product.

(d) Provide automated (easy-to-use) software for customers to use AASAP in conjunction with ERDAS.

(e) Develop and execute a credible marketing approach and strategy.

(f) Demonstrate the flexibility in using the AASAP subpixel process for a variety of different applications.

(g) Use commercial-off-the-shelf (COTS) hardware (workstations), software, and imagery (like LANDSAT TM and SPOT MS).

(h) Demonstrate the ability and ease to integrate the AASAP detections with commonly used GIS procedures.

1.3 Scope.

The AASAP process has been under development for ten years. It is the next logical step to improve traditional classification techniques by improving the discrimination level of available remote sensing data. The improved discrimination level from whole pixel (traditional classification techniques) to subpixel provides the end user with a new capability to solve problems.

2.0 APPROACH TO COMMERCIALIZATION:

AAI, as a small company of thirteen people, realized that they could not effectively market and sell the product themselves. The AAI company team had minimal marketing/sales experience and was also constrained by the limited amount of funds that could be spent in this area. Over a period of time a decision was made to negotiate a third party software agreement with ERDAS, Inc. ERDAS had a widely accepted, powerful image analysis and manipulation software product, called IMAGINE, that AAI could smoothly integrate with. The IMAGINE software accomplished the traditional whole pixel image classification processes, and the AASAP subpixel process was a logical extension to provide higher levels of discrimination and accuracy. The seamless integration with IMAGINE, with the same look and feel, resulted in a smooth transition for the IMAGINE users to learn and use AASAP. The thrust here was to make it easy and comfortable for the ERDAS IMAGINE user to use AASAP. This was accomplished by using as much of the IMAGINE functionality as possible as inputs and output into the AASAP process and to make the AASAP windows look like the IMAGINE windows. As a result of this tight integration with the ERDAS IMAGINE software, the beta site users were trained and using AASAP in less than one-half day.

AAI made a concerted effort to demo and make presentations of the product at the large conferences in conjunction with ERDAS, for example, GIS/LIS, ASPRS, and DMA Industry Days for government accounts. AAI also demonstrated AASAP at universities; ERDAS, SPOT, and EOSAT Users Group Conferences; PERS Regional Workshops; Product Evaluation Panel Workshops; and countless demos at AAI's facility. Articles were published in the Earth Observation Magazine and in the IEEE Spectrum Magazine. All the above activity was planned about one year ahead of launching the product.

The pricing of the product was accomplished in concert with ERDAS and was established to be attractively priced in consideration of similar type add-on modules. The price was set at $5,500 per license, which includes the first year of software support. Software support for subsequent years is $500 for the first license and $250 for each additional license. An introductory price of $4,125 is offered, which is 25% off the list price. A standard discount of 20% was offered to government organizations (exclusive of the introductory offer). Discounts for 2-5 licenses is offered at 25% off the list price, and six licenses and above at 50% off the list price. This pricing is consistent with the ERDAS pricing strategy and is well known to ERDAS users.

The major market penetration approach was through ERDAS to their current domestic and international customer base. ERDAS was selected as a beta site and some of their key personnel were trained at an early stage on AASAP. Other conferences, sales meetings, user group meetings, and exchange meetings between the two companies provided ample opportunity for ERDAS personnel to learn the AASAP subpixel process. Additionally, the AASAP subpixel capability will generate sales to customers that have hard problems that were not solvable with traditional image processing techniques. AAI recognized that their established presence in the military/intelligence market will provide some assistance in selling those customers on an advanced remote sensing image processing technique. Some of these military/intelligence customers have used the traditional image processing techniques, and the spatial resolution of the sensor data was not adequate for their problems. The AASAP subpixel process effectively improves the discrimination level of LANDSAT or SPOT by a factor of four to five. As such, with no change in the sensor or other ground data processing techniques, the automated AASAP subpixel process now offers a new dimension to solve these more difficult problems without the use of a photo-interpreter. The end result is an effective means to accomplish broad area searches in a passive mode.

ERDAS, in coordination with AAI, will launch the product with a combination of press releases and a direct mailing to the ERDAS customer base. The ERDAS sales force and distributors will follow-up with targeted accounts, both domestically and internationally. AAI will make direct contact with selected military/intelligence users as well as the ERDAS military sales group.

3.0 RESULTS:

3.1 Business Results.

The AASAP subpixel product is being launched during the summer of 1995. It is expected that sales will not start materializing until the fall of 1995. The initial buyers of AASAP subpixel licenses will most likely be research organizations (commercial, government, and universities) who are interested in continually improving the discriminating capability of their remote sensing products. It is anticipated that the international market will generate early interest, particularly with the quasi-governmental space/remote sensing organizations. As the product is accepted in the remote sensing marketplace, the more general commercial (production related) ERDAS IMAGINE users will start to buy the product.

The existing market is over 7,000 ERDAS IMAGINE licenses, which is growing at 10-15% per year. Since AASAP is an add-on module to the IMAGINE product line, providing higher levels of discrimination and accuracy, there is an opportunity to sell the subpixel product to most of these users. The product is a natural extension to the ERDAS IMAGINE whole pixel classifiers, whereby the user easily selects the subpixel process icon off the main menu and the image is in a subpixel classification mode using many familiar ERDAS IMAGINE functions. The User's Guide documentation has been tested and updated for over two years, and it has received high marks from commercial, government, and university users.

The revenues anticipated in 1995 will be modest as the product is carefully released in the marketplace. Gradual acceptance is critical with the selected first users. Further improvements on the speed of the software will be a factor in an increase of sales in 1996. To date, the product has been under acceptance testing at ERDAS and no product has been delivered. The first sale is pending with delivery in September to a research organization in Germany. The answers to Business Development Related Questions are contained in Exhibit 2.

3.2 Technical Results.

The most important development of the product was the automation of the signature derivation module, which allows users to develop their own signatures on their workstations. This occurred in conjunction with the EOCAP II contract. The second most significant development of the product was the automation of the atmospheric correction factor, which permits the user to use signatures developed in one scene to be used in any other scene allowing the transferability of signatures.

The extensive accuracy assessment funded under the EOCAP II contract was the critical link to establishing the credibility of the AASAP product. The accuracy assessment of the cypress, tupelo, and loblolly pine species enabled AAI to actively promote the verifiable improvement by using the AASAP product in comparison to traditional whole pixel classifiers, like minimum distance, maximum likelihood, etc. The accuracy assessment was performed by Clemson University and the U.S. Forestry Service with extensive field measurements to

Business Development Related Questions

1. **What developments, changes, new attitudes, etc. have you seen in the markets that are relevant to your EOCAP II project since you started it? These can include changes in market demand, changes in government policy, changes in data, and hardware prices, etc.**

   The marked advancement is faster UNIX computer workstations with substantial increases in memory for image processing with a corresponding decrease in the prices of these powerful machines. This could not have been forecasted in 1990 when AAI put the EOCAP II proposal together. As a result of these dramatic positive changes in the marketplace, AAI changed its product strategy from a service bureau type of operation to a licensed software product where the user can develop material signatures automatically and accomplish the related image processing on the user's own computer workstation. This will result in a much wider demand for the AASAP subpixel product and paved the way for the third party arrangement with ERDAS to promote, market, and sell AASAP.

2. **What are your expectations about changes in the markets that are relevant to your EOCAP II project between now and 1996? Between now and the long-run (pick a time period of your choice - say 2000 or 2010)?**

   The changes in the marketplace between now and 1996 will be the availability of remote sensing image products on PCs. The improvements in the PC software and significant increases in speed and disk space will introduce remote sensing capabilities to a whole new customer base. The expected changes between 1996 and the year 2000 will be the availability of the abundance of new lower priced commercial remote sensing image products. These new multispectral image products will be higher resolution with three to four bands. The AASAP subpixel capability will always be able to provide further improvements in resolution without regard to the resolution of the sensor and provide the unique material pixel fraction information. Additionally, the introduction of satellite hyperspectral imagery will be available before the year 2000, and AAI has a hyperspectral process "BANDS", which is in alpha testing with solid performance results. The "BANDS" software process also reduces the high data processing burden by selecting the diagnostic information by band location. AAI plans to be the leader in hyperspectral image processing and be in the position to provide a corollary product by 1997.

Exhibit 2
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3. **What are the sources of uncertainty you face as you continue commercial remote sensing efforts or that you faced if you have discontinued these efforts? Uncertainty may relate to business risk, technical risk, data unavailability, legal and regulatory hurdles, government policy, funding, etc.**

The area of uncertainty is the quality of the data from these planned new remote sensing products. It is highly important that the band-to-band registration integrity be maintained. Also, the other area of uncertainty is the acceptability of the AASAP product by the user community. The AASAP subpixel product is easy to use and is seamlessly integrated with ERDAS IMAGINE, however, the user has to accomplish some additional actions that are not part of a traditional classification effort. The concern here is not with the more sophisticated user, but is the AASAP subpixel product reaching the average less sophisticated ERDAS IMAGINE user? AAI has planned some product improvements to address these areas that should be available in the next software release in January 1996.

4. **Have you been able or do you expect to reap any productivity gains in your company as a result of EOCAP II? If so, could you quantify them, to the extent possible, in terms of dollars saved per year or per unit of output?**

As a combined effort with the EOCAP II project and other related efforts in the company, the signature development and scene-to-scene processing has been automated to the extent that less skilled personnel can now accomplish these actions as well as doing it much faster.

a. <u>Productivity Gain</u>: The signature development and scene-to-scene processing can be done in about one-fourth the time as previously accomplished and by personnel making about one-half the salary.

b. <u>Rough Estimate of Annual Cost Savings</u>: $56,000 per year plus the ability to take on more projects and complete them on a timely basis.

5. **Please share with us any other developments related to EOCAP II that might be significant to us in managing EOCAP or communication success in the industry to policymakers. Examples are new jobs/divisions created within your company, patents, articles in peer-reviewed or other journals or the trade press (please give us citations or better yet, provide us copies if you can spare them).**

The company almost doubled in size from the start of the EOCAP project through its completion (7 to 13). Also, the company upgraded its computer workstation capability by a factor of 10.

Exhibit 2
Page 2 of 3

Articles published include:

a. Earth Observation Magazine, July 1994, titled: "Subpixel Analysis - Process Improves Accuracy of Multispectral Classifications."

b. IEEE Spectrum Magazine, March 1995, titled "Remote Sensing."

c. Articles submitted to PERS (Photogrammetric Engineering and Remote Sensing Magazine) and to the GIS Europe Magazine.

6. Do you have any bones to pick with how EOCAP is managed, public policy relating to EOCAP, or any other issues?

No. AAI has appreciated the frank, honest, and helpful approach the NASA team has rendered.

7. Is there anything else you'd like to report about EOCAP - pro or con - from the past year?

Yes. I think that one problem small companies have is raising the capital to buy advanced computer workstations and related equipment/software tools. It would be helpful if, through the EOCAP, that a provision would be made for small companies to lease these more powerful machines and to acquire advanced software tools. Also, a seminar/workshop sponsored by EOCAP using their internal capabilities and/or inviting potential suppliers would be very helpful. This could be done on an annual basis, maybe during the annual review process at SSC.

Exhibit 2
Page 3 of 3

confirm that the different species were detected or that detections were made of other species (commission error) or that the MOI species were missed (omission error). The accuracy assessment was a highly involved process which included warping the LANDSAT TM image to aerial photographs and USGS 7.5' minute map sheets, as well as using GPS devices to confirm exact geographic locations. Pixels were randomly selected over a number of image locations to determine the accuracy. The total classification accuracy for each specie was:

Tupelo:	91%
Cypress:	89%
Loblolly Pine:	88%

Outside the signature training set areas, the performance of AASAP dropped by approximately 5%, but the traditional classification techniques dropped up to 50%. In other words, using traditional techniques, most pixels of the interested tree species were not detected and pixels containing other tree species were detected, which resulted in a substantial amount of confusion.

4.0 POST-EOCAP II ACTIVITIES:

Further product development activities include: (a) speed improvements planned to be incorporated in January 1996 for both classification and signature derivation; (b) incorporation of an automatic cloud sampler eliminating the need for the user to draw ERDAS IMAGINE Areas of Interest (AOIs), which results in a qualitative decision of pixels that contain clouds; (c) incorporation of a signature editor, which will allow the user to view and compare the signature spectrum; (d) Quantitative Image Characterization (QIC), which will allow the user to classify the image with multiple signatures simultaneously instead of one-at-a-time; (This is a major effort which is planned for release in the fall of 1996. It is envisioned that the user will have the option of working in the traditional one signature mode or selecting the QIC multiple signature mode); (e) incorporating a hyperspectral capability using AAI's BANDS software program. This hyperspectral capability is under alpha testing, and a release is planned for early 1997. This will be a significant functionality add-on to the multispectral capability.

In the marketing area, AAI and ERDAS plan to run an ad in the Earth Observation Magazine with a press release and direct mailing to U.S. ERDAS IMAGINE users in the summer of 1995. The penetration of the international market is planned for the October/November 1995 time frame with presentations in Germany to the European/African/Middle East ERDAS Users Group Meeting and to the ERDAS international distributors. Some of the product improvements will also help the average ERDAS IMAGINE user feel more comfortable in using an advanced classifier like the AASAP subpixel process. AAI is scheduled to present papers and exhibit the AASAP software with ERDAS at the following major remote sensing/GIS conferences: EOSAT Seminar, Denver, Colorado, October 1995; GIS/LIS, Nashville, Tennessee, November 1995; ASPRS/ACSM Annual Convention, Baltimore, Maryland, April 1996.

5.0 LESSONS LEARNED FROM EOCAP II:

AAI learned a hard lesson in not being thoroughly customer/market focused in the beginning of the EOCAP II program. The EOCAP II evaluators greatly helped AAI in re-looking at the market and adjusting the product based on changing market conditions. The Product Evaluation Panels (PEPs) were extremely helpful in generating interaction with the potential customers as well as receiving valuable inputs that resulted in a modified enhanced product. One area that could have helped AAI, being a very small company, would be an expansion of the EOCAP to assist companies in borrowing, leasing, or acquiring relatively expensive UNIX workstations.

APPENDICES:

A. LANDSAT TM imagery of wetlands classification in South Carolina.

1. Scene 201 is a TM image unprocessed with AASAP where the wetlands is grossly outlined in the middle of the scene in pink. The light blue/white areas are open fields and the dark areas are mostly pine trees.

2. Scene 202 is the same area classified with AAI's subpixel process. The yellow detections are whole pixels, and the red detections are subpixel detections of tupelo trees. The subpixel detections provide a fine level of discrimination indicating wetland areas not classified by traditional classification techniques.

3. Scene 203 is the same scene illustrating discrimination between tupelo and cypress trees using the AASAP subpixel process. The red pixels contain both cypress and tupelo trees.

4. Scene 204 shows the tupelo tree detections overlaid onto a standard USGS Quad Map. Additionally, the amount of tupelo trees is displayed in the color coded legend indicating 76-100%, 51-75%, and 25-50% of the tupelo trees in the detected pixels.

5. Scene 205 shows the AASAP classification of each of the five wetland tree species.

6. Scene 206 shows the AASAP classification of the five wetland tree species draped over a Digital Elevation Model (DEM) to illustrate how AASAP output can be used in a GIS or for post-processing. The wetland areas are in the depressions between the steep topographic areas.

B. LANDSAT TM imagery of pine tree plantings in the Savannah River Site in South Carolina.

1. In Scene 301 the loblolly pine trees are detected by the yellow indicators on the image. This is a rather hard problem in that loblolly is being detected from longleaf and slash pines.

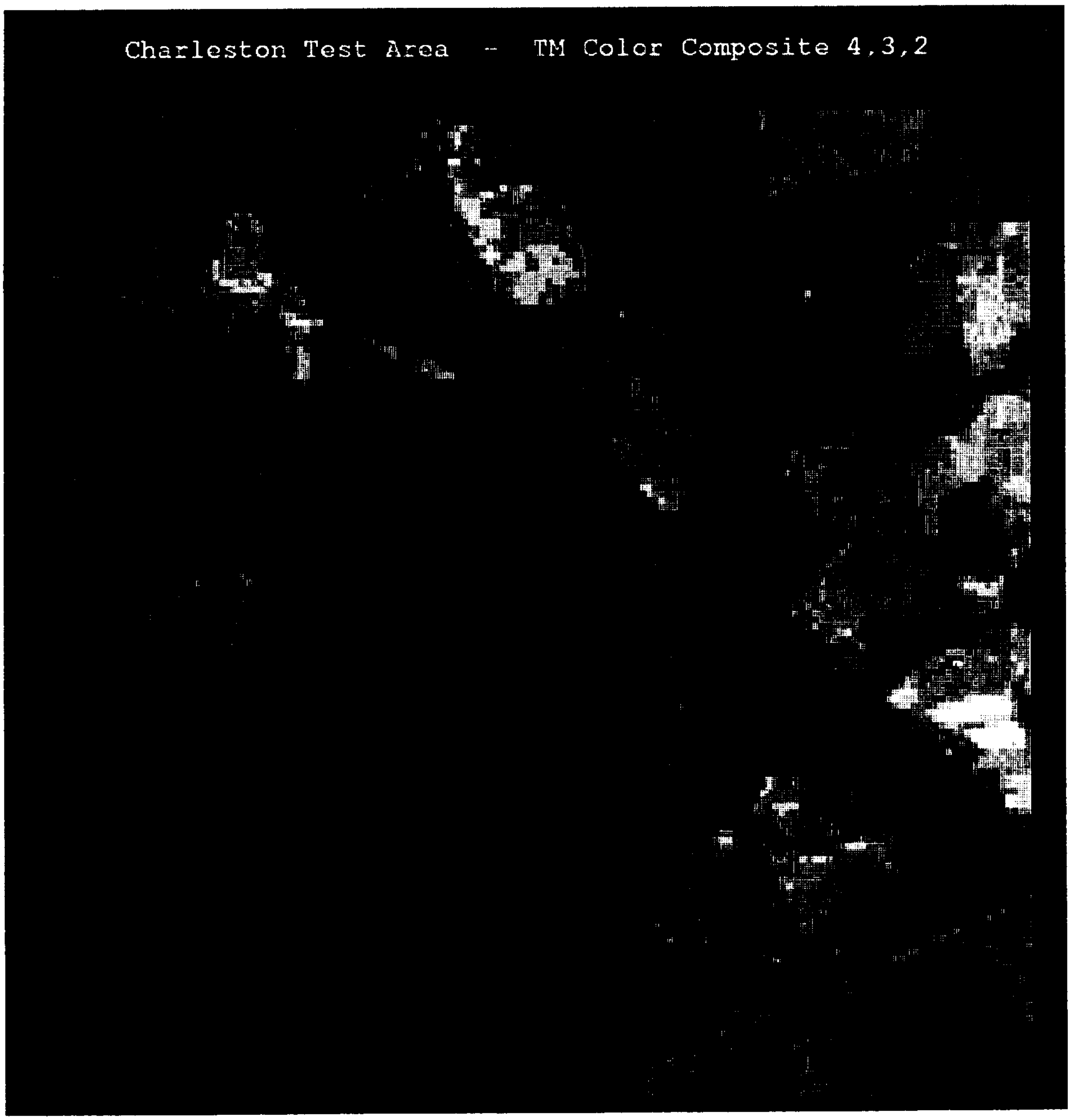
2. In Scene 302 the loblolly detections are overlaid onto a USFS stand map of the area. Individual pine stands appear as polygons, color coded according to what specie was planted and the percent area of the stand which is loblolly. This map can be used by resource managers to determine where the densest loblolly stands are and how much loblolly occurs in non-loblolly stands. In many cases, the amount of loblolly which had been infiltrated into non-loblolly stands had been under-estimated.

3. Scene 303 shows the loblolly pine classification displayed in the ERDAS IMAGINE software. The AASAP module icon is the bottom icon on the icon panel, and the AASAP material pixel fraction information is displayed in the IMAGINE color legend.

Appendix A

MAY 1992 LANDSAT TM SCENE

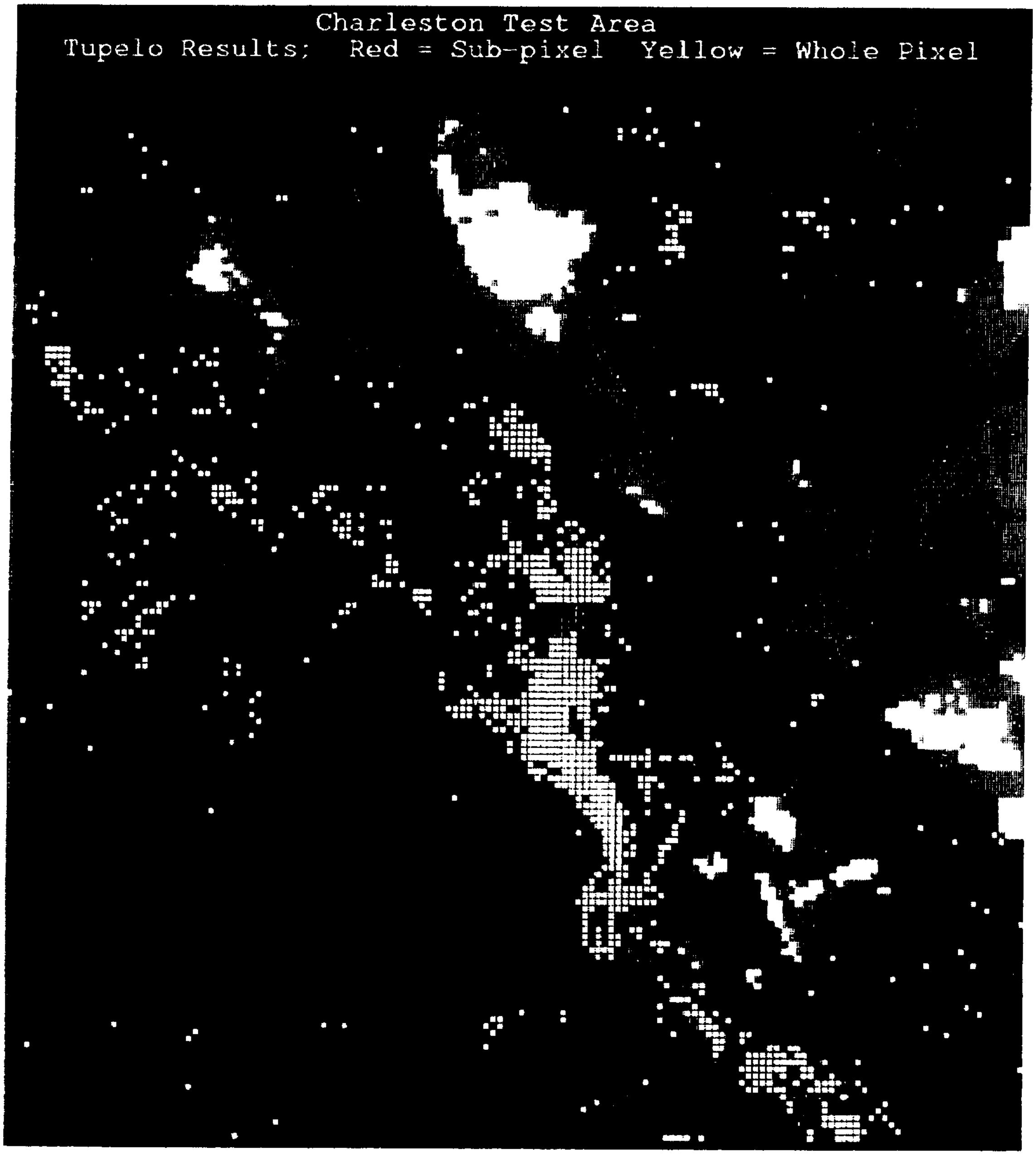
CHARLESTON, SOUTH CAROLINA
WETLANDS AREA



Scene 201
Applied Analysis Inc.
46 Manning Road
Billerica, MA 01821

Appendix A
MAY 1992 LANDSAT TM SCENE

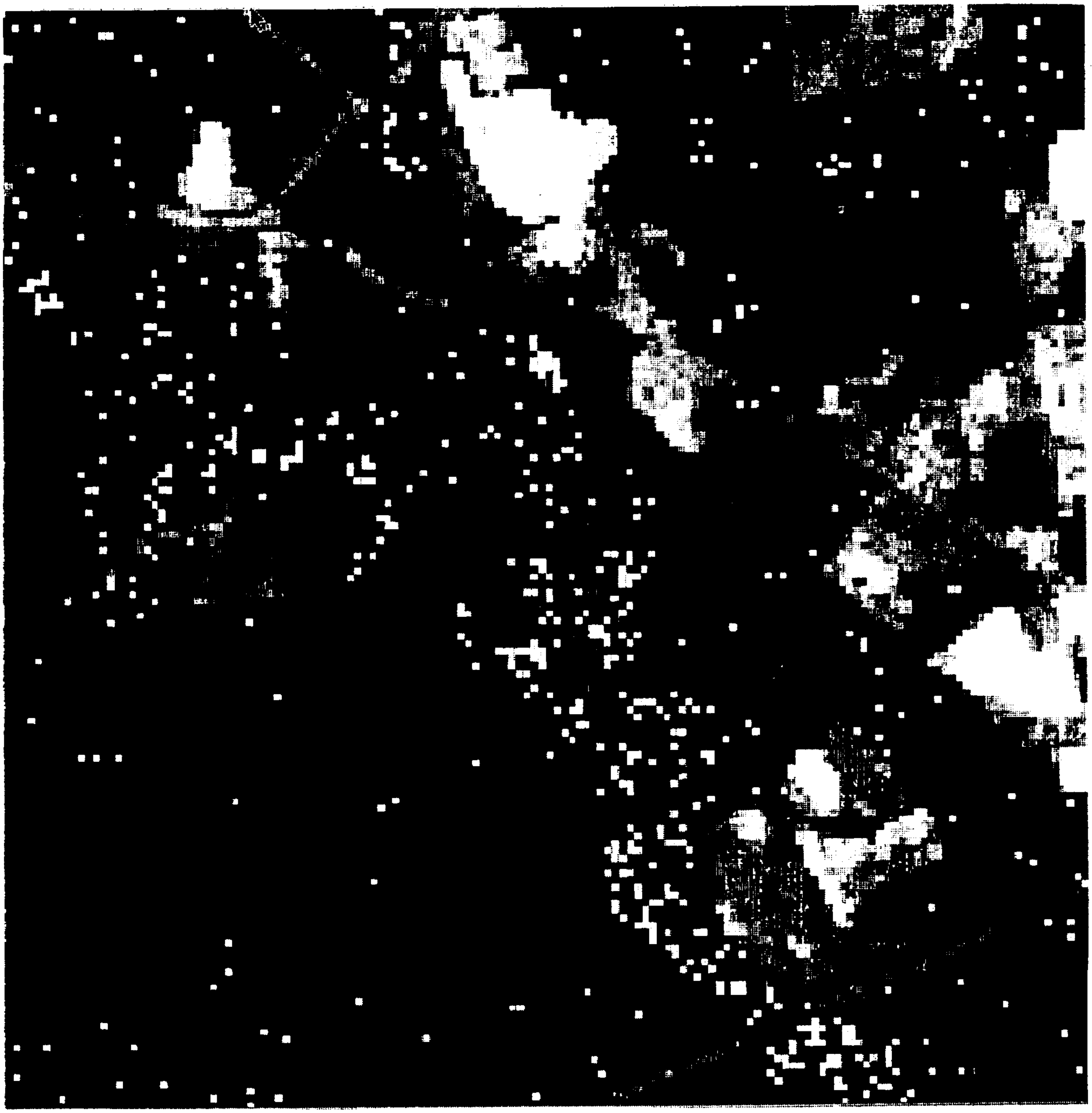
CHARLESTON, SOUTH CAROLINA
WETLANDS INDICATOR SPECIES DETECTIONS



Scene 202
Applied Analysis Inc.
46 Manning Road
Billerica, MA 01821

Appendix A

AASAP TUPELO AND CYPRESS RESULTS



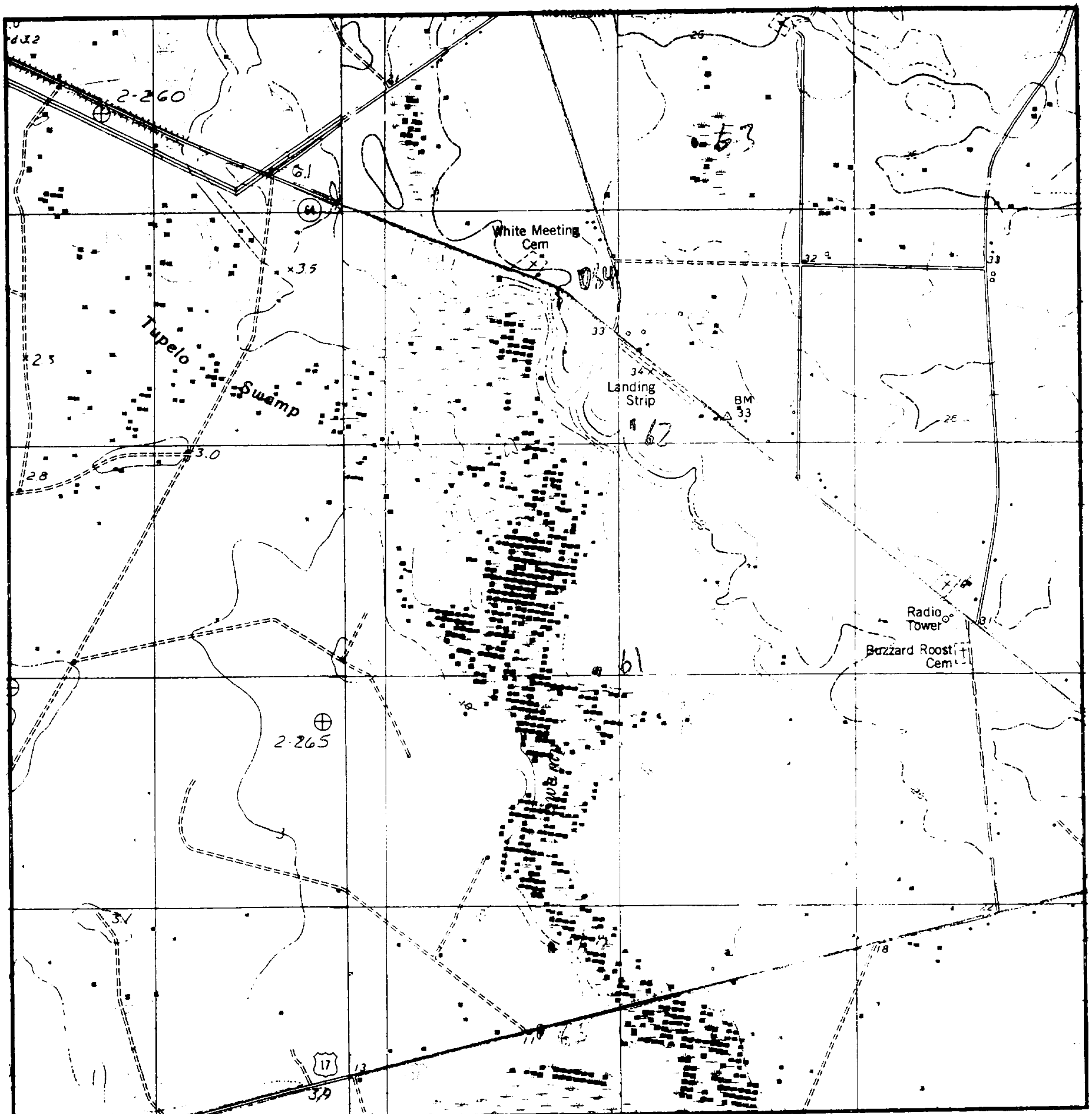
Scene 203

YELLOW = TUPELO
BLUE = CYPRESS
RED = TUPELO AND CYPRESS

APPLIED ANALYSIS INC.
40 MANNING ROAD
BILLERICA, MA 01821

Appendix A

AASAP TUPELO DENSITY MAP



Scene 204

Legend

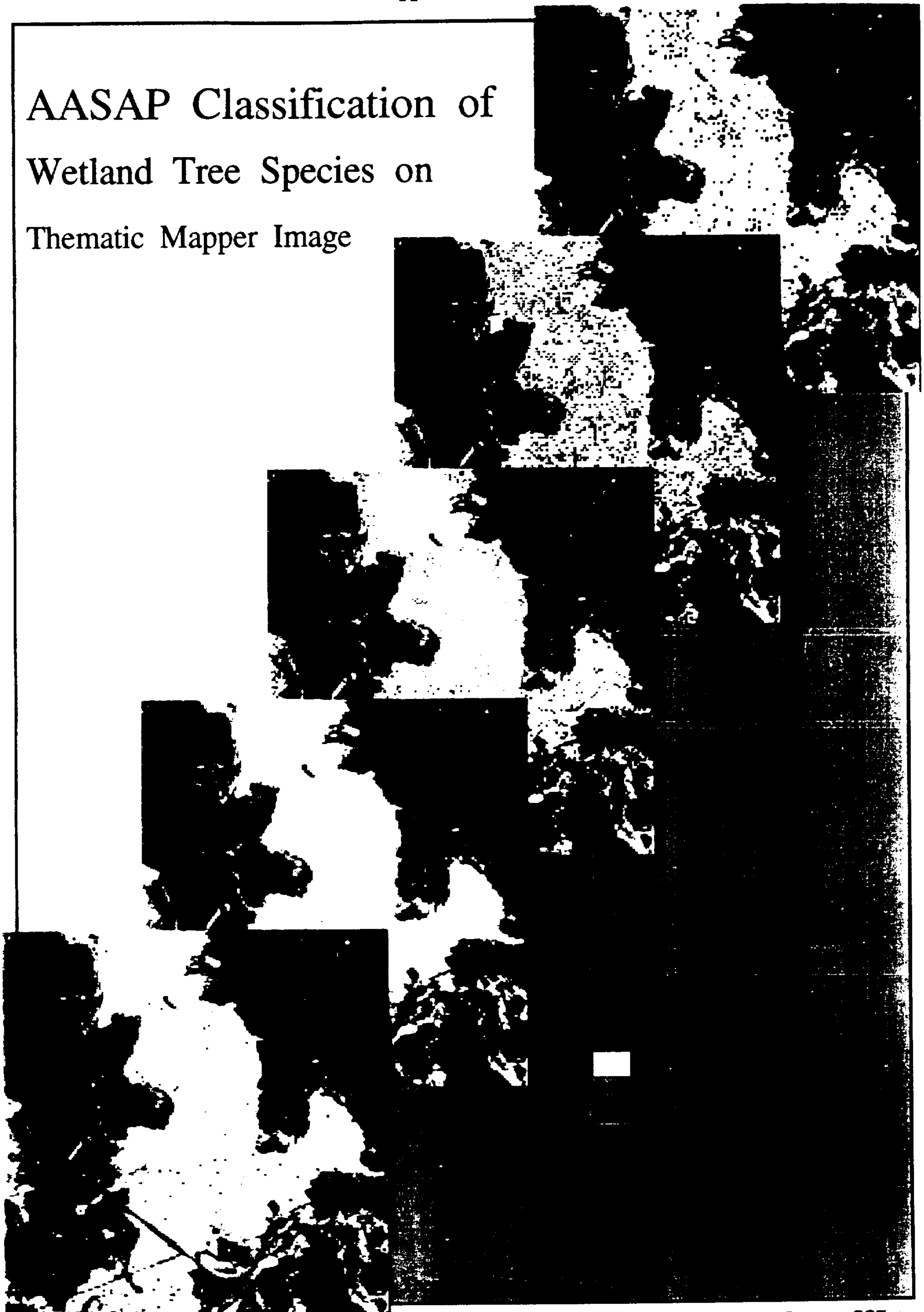
- ***76 - 100 % tupelo***
- ***51 - 75 % tupelo***
- ***25 - 50 % tupelo***

AASAP Tupelo Classification: 91% total accuracy

Base map: 1:24,000 topographic map

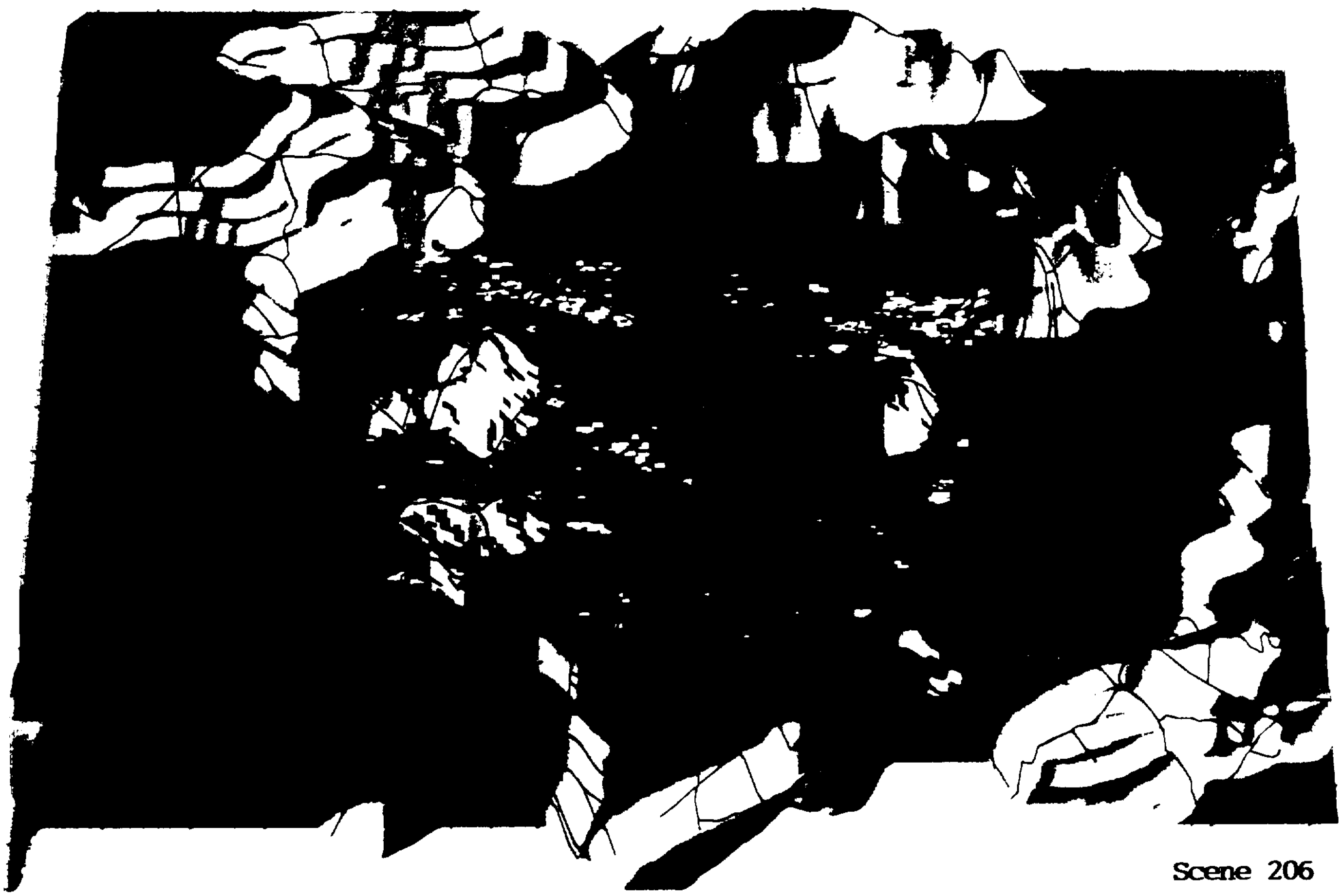
Prepared by: Applied Analysis Inc. and Clemson University

AASAP Classification of Wetland Tree Species on Thematic Mapper Image



Scene 205

Appendix A



Scene 206

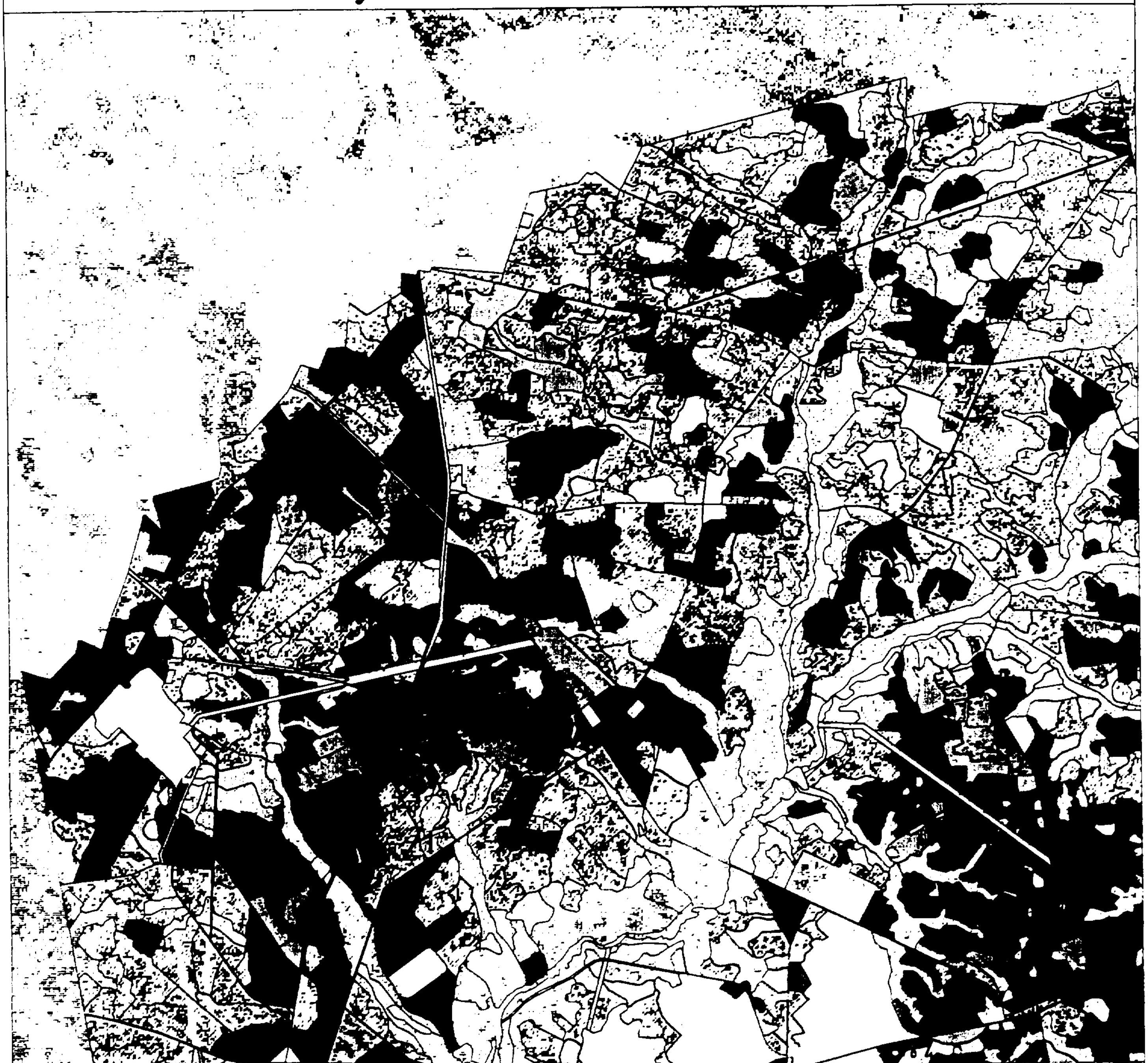
Appendix B

CLASSIFICATION OF LOBLOLLY PINE AT THE SAVANNAH RIVER SITE

Scene 301

Applied Analysis Inc.
Billerica, Massachusetts

Percent Loblolly in U.S. Forest Service Pine Stands



Dots denote TM pixel locations classified as loblolly pine

February 16, 1995

Scene 302

Stand Classification	Percent Loblolly Detected
longleaf	0 - 20%
longleaf	20 - 100%
slash	0 - 20%
slash	20 - 100%
loblolly	0 - 30%
loblolly	30 - 60%
loblolly	60 - 100%

Stand data taken from the USFS Savannah River Site GIS database

SUBPIXEL CLASSIFICATION OF LOBLOLLY PINE USING ERDAS IMAGINE AND AASAP

The Applied Analysis Spectral Analytical Process (AASAP) was used to classify loblolly pine in a U.S. Forest Service forest within the Savannah River Site in South Carolina, where discrete, well defined stands of various species of southern yellow pine were planted. Although only one species was planted in each stand, through time, aggressive species like loblolly infiltrated many non-loblolly stands. The AASAP subpixel classifier was used to accurately identify pixels containing loblolly. The classification results and a digital U.S.F.S. stand map were used in a GIS to quantify the amount of loblolly in each stand and 170 randomly selected pixels were field verified to independently evaluate errors of omission and commission. The total classification accuracy was 88% (91% omission accuracy and 85% commission accuracy). A kappa coefficient can not be calculated for a subpixel classification accuracy assessment because a single pixel can be correctly classified into more than one class.The results indicate that there are many non-loblolly stands which contain greater than 20% loblolly.

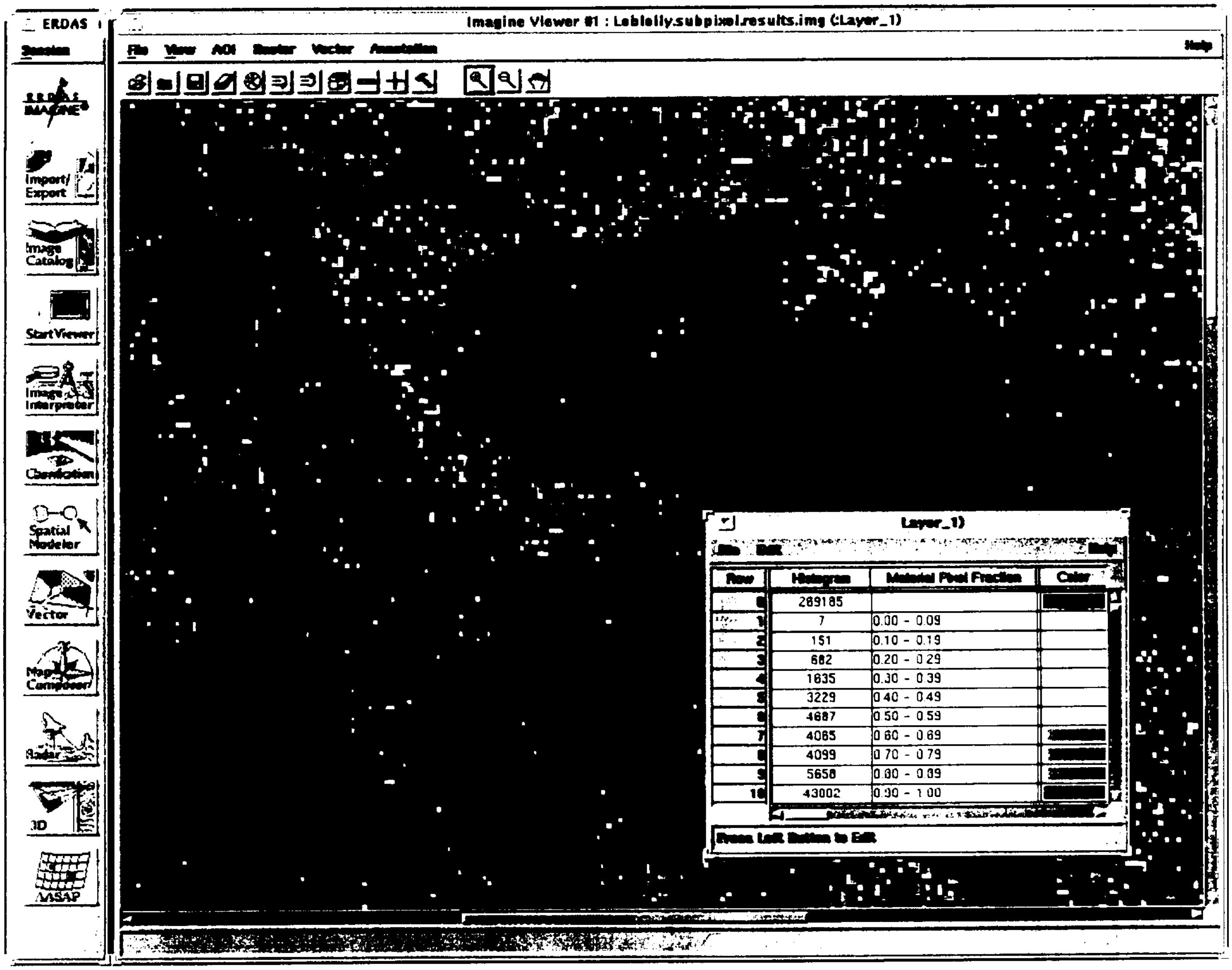
This map shows the loblolly classification on the U.S.F.S. stand map. The TM pixels classified as containing loblolly appear as small black dots. Individual pine stands appear as polygons color coded according to what specie was planted and the percent area of the stand which is loblolly. This map can be used by resource managers to determine where the densest loblolly stands are and how much loblolly occurs in non-loblolly stands. In many cases, the amount of loblolly which had infiltrated into non-loblolly stands had been underestimated by the U.S.F.S.

The ERDAS IMAGINE Spatial Modeler was used to create the images above. The AASAP subpixel classifier is a module in ERDAS IMAGINE and all processing used to create the maps above was accomplished within ERDAS IMAGINE. The AASAP subpixel classifier can be used to classify a wide variety of natural resource and man made materials in multispectral imagery.

Clemson University
Strom Thurmond Institute
Clemson, South Carolina

Applied Analysis Inc.
Billerica, Massachusetts
Contact: Don Damm (508) 663-6828

Appendix B



Scene 303

APPENDIX C

TECHNICAL PAPER

DESCRIBING

AASAP CLASSIFICATION OF WETLAND AND FORESTRY SPECIES

SUBMITTED FOR PUBLICATION IN

<u>PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING</u>

Subpixel Classification of Bald Cypress and Tupelo Gum Trees in Thematic Mapper Imagery

Robert L. Huguenin
Mark A. Karaska
Applied Analysis Inc.
46 Manning Road, Suite 201
Billerica, MA 01821

Donald Van Blaricom
Basil Savitsky
Strom Thurmond Institute
Clemson University
Clemson, SC 29634

John R. Jensen
Dept. of Geography
University of South Carolina
Columbia, SC 29208

Subpixel Classification of Bald Cypress and Tupelo Gum Trees in Thematic Mapper Imagery

Abstract

A 'subpixel spectral analytical process' was used to classify Bald Cypress and Tupelo Gum wetland in Landsat Thematic Mapper imagery in Georgia and South Carolina study areas. The subpixel process enabled the detection of Cypress and Tupelo trees in mixed pixels. Two hundred pixels were field verified for each tree specie to independently measure errors of omission and commission. The cypress total accuracy was 89% and the tupelo total accuracy was 91%. Field investigations revealed that both cypress and tupelo trees were successfully classified when they occurred both as pure stands and when mixed with other tree species and water.

1. Introduction

Scientists have been trying to extract wetland information from Landsat Multispectral Scanner (MSS) imagery since 1972, Landsat Thematic Mapper (TM) imagery since 1982, and SPOT multispectral data since 1986 (Hodgson et al., 1988; Jensen et al., 1995). Investigators have successfully inventoried large monospecific stands of wetland plant species using pattern recognition image classification techniques. However, heterogeneous wetland containing several plant species plus standing water often cannot be classified correctly with the 80 x 80m, 30 x 30 m, and 20 x 20 m spatial resolution remote sensor data. The per-pixel classification algorithms simply cannot disaggregate the individual materials of interest within the instantaneous-field-of-view (IFOV) of the sensor system.

For example, consider the hypothetical but representative TM pixel data shown in Figure 1 that contains approximately equal percentages of cypress (33%), tupelo (33%), and water (33%). Table 1 and Figure 1a reveal that the integrated digital number (DN) value output of this pixel in six bands (the TM thermal band 6 is excluded from discussion) will be substantially different than any of the spectral reflectance spectra associated with 'pure' cypress, 'pure' tupelo, and 'pure' water land cover. The integrated 'mixed pixel' usually causes classification confusion and prohibits the classification of individual materials of interest with traditional classifiers because the mixed pixel composite spectral signature is unlike the spectral signature of the individual surface materials occurring as subpixel components.

Table 1. Hypothetical Landsat Thematic Mapper data of five 30 x 30 m pixels containing, respectively, pure cypress, pure tupelo, pure water, and equal proportions of cypress, tupelo, and water.

TM Bands	Cypress (pure)	Tupelo (pure)	Water (pure)	Tupelo (33%) + Water (33%)	Cypress (33%) + Tupelo (33%) + Water (33%)
1	21	27	24	17	24
2	18	15	21	12	18
3	33	27	12	13	24
4	48	42	9	17	33
5	42	33	6	13	27
7	39	27	3	10	33

Individual wetland plant species and surface materials which occur as subpixel components in TM mixed pixels have the potential to be spectrally resolved and classified using subpixel processing techniques that can distinguish surface materials smaller than the spatial resolution of the sensor. This paper first briefly describes the subpixel image classification process, (Applied Analysis Spectral Analytical Process - AASAP). A detailed description of the process will be presented in a separate paper. The process is then applied to classify wetland Bald Cypress ***(Taxodium distichum)*** and Tupelo Gum *(Nyssa aquatica)* in TM imagery of South Carolina and Georgia study areas (Barry, 1980). The results of an extensive accuracy assessment involving global positioning system (GPS) field verification of 200 pixel locations for each tree specie is also presented .

2. Subpixel Processing

Many wetland mapping applications have not been seriously affected by the mixed pixel problem because analysts have convinced themselves that they can be satisfied by labeling 'mixed pixels' with 'mixed labels'. For example, while it would be wonderful to identify the exact proportion of a pixel containing 70% cypress and 30% tupelo, most wetland scientists simply call the class 'mixed cypress-tupelo' because they have no mechanism for extracting information about the proportion of individual materials of interest using traditional per pixel classification logic. The traditional classifiers have generally performed well for classifying very large, monospecific stands of tree species, but they have not been successful in the identification of the proportions of several materials of interest found within the IFOV of a sensor system (Jensen et al., 1995).

Thus, there is the need for ***subpixel processing***, defined as the digital search for specific materials-of-interest (MOI) from within a pixel's mixed multispectral image reflectance spectrum. Subpixel processing does not provide information on *where* the material of interest (MOI) occurs within the pixel. It does provide important information on the relative proportion of the material-of-interest found within a pixel (e.g. this pixel contains 73% cypress). The logic of subpixel processing is discussed and applied to wetland environments in Georgia and South Carolina. However, it is applicable to any mixed pixel problem such as monitoring residential development at the urban fringe or mapping suspended sediment loads in water bodies.

2.1 How the Subpixel Processor Works

The general subpixel processing steps are summarized in **Figure 2**. First, unrectified multispectral remote sensor data is processed to remove atmospheric radiance and attenuation effects. Then, a signature is derived for a material of interest (MOI). Each pixel is then classified as to its fraction of material of interest present. For example, if the MOI is cypress, each pixel in the scene will contain a number from 0 to 1.0 identifying the proportion of cypress within the pixel. Information about the various stages are presented below.

To address the mixed pixel problem, the subpixel processor assumes that each image pixel, $\mathbf{P_m}$, contains some fraction, $\mathbf{f_m}$, of the material of interest, M, (e.g. cypress), and the remainder, $\mathbf{1-f_m}$, contains other background materials, $\mathbf{B_m}$:

$$\mathbf{P_m} = (\mathbf{f_m} \times \mathbf{M}) + [(\mathbf{1-f_m}) \times \mathbf{B_m}] \qquad (1)$$

In Figure 1, if cypress were the material of interest (M), then $\mathbf{f_m}$ would equal 1/3 and the remainder of the background surface cover materials ($\mathbf{B_m}$) would be $\mathbf{1-f_m}$ or 2/3. In Equation 1, **M** is a single specified material of interest such as cypress. The value $\mathbf{B_m}$ in Equation 1 refers to all of the other materials in the pixel, treated as a single combined set of "background" materials. The value $\mathbf{f_m}$ is always an areal fraction. Equation 1 assumes that **M** is invariant from pixel to pixel, while $\mathbf{P_m}$, $\mathbf{f_m}$, and $\mathbf{B_m}$ can vary from pixel to pixel. In this paper we report results for two materials, cypress and tupelo. It is important to remember that each material was searched for independently, i.e. in one analysis **M** was cypress and in another analysis **M** was tupelo.

For the applications reported here, **M** and $\mathbf{B_m}$ are assumed to be optically thick in at least one of the spectral bands. Therefore, the radiant contributions from **M** and $\mathbf{B_m}$ are assumed to be approximately linearly additive in spectral bands, n:

$$\mathrm{R_m[n]} = (\mathrm{k_m[n]} \times \mathrm{T[n]}) + ((1-\mathrm{k_m[n]}) \times \mathrm{N_m[n]}) \qquad (2)$$

where, $\mathrm{R_m[n]}$, $\mathrm{T[n]}$, and $\mathrm{N_m[n]}$ are the radiances from $\mathbf{P_m}$, **M**, and $\mathbf{B_m}$ in pixel **m** and band **n**, respectively. $\mathrm{k_m[n]}$ is the radiant fraction contributed by $\mathrm{T[n]}$ in pixel **m** and band **n**.

To use Equation 2 to search for the materials of interest, the raw digital number values for pixel **m**, i.e. $DN_m[n]$, are corrected for atmospherically scattered solar radiance, atmosphere attenuation of incident and reflected solar radiance, illumination and sensor look angles, and the sensor multispectral transfer function. An environmental correction module uses sampled pixels from the scene being processed to automatically derive the correction factors (**Figure 2**). An offset spectrum **ARAD[n]** is derived that includes the needed additive correction. A gain factor spectrum, **SF[n]**, includes the needed multiplicative corrections. Applications of these two factors to the pixel $DN_m[n]$ yields the equivalent integrated in-band, bi-directional reflectance of the materials in the pixel:

$$r_m[n] = \frac{DN_m[n] - ARAD[n]}{SF[n]} \qquad (3)$$

which provides the requisite proportionality to $R_m[n]$ in Equation 2. **ARAD[n]** and **SF[n]** are scene specific, and are assumed to be invariant from pixel to pixel within the scene. Pixel to pixel variations of haze and other environmental factors may not be directly compensated for by these factors.

During the classification process, the subpixel processor applies the **ARAD[n]** and **SF[n]** factors to $DN_m[n]$ for each pixel under investigation to transform it to a spectrum that is proportional to $R_m[n]$ in Equation 2. **T[n]** in Equation 2 is provided by the reference spectral signature for the material of interest. The two unknowns in Equation 2, $k_m[n]$ and $N_m[n]$, are then solved for by an intelligent background identification process that selects an appropriate $N_m[n]$ for the pixel and then solves for $k_m[n]$.

The process for determining the appropriate $N_m[n]$ for the pixel under investigation uses the spectral difference between $R_m[n]$ and $T[n]$ to intelligently characterize a set of spectral requirements on $N_m[n]$ and $k_m[n]$. The process then automatically searches the image for candidate pixels that satisfy these requirements. A processing module provides a characterization of the image that limits the search and the number of $N_m[n]$ candidates that are tested per pixel. The best $N_m[n]$, $k_m[n]$ candidate pair is selected by solving Equation 2 for the material of interest spectrum in pixel **m**, i.e.:

$$T_m[n] = (R_m[n] - ((1-k_m[n]) \times N_m[n])) / k_m[n] \qquad (4)$$

and comparing the $T_m[n]$ with the reference signature for the material of interest, $T[n]$. After selecting $N_m[n]$, Equation 3 is then solved for $k_m[n]$ and transformed to the derived scalar fraction, k_m, for pixel m. The value k_m is the final output reported by the subpixel processor.

2.2 Obtaining the Training Signature of the Material of Interest (MOI)

The reference training signature for the material of interest, $T(n)$, is obtained using a signature derivation module (**Figure 2**). A set of training pixels is identified that is known to contain the material of interest, M. The fraction of each training pixel that contains the material of interest is estimated. This is specified as an estimated mean fraction for the training set and is assigned to all of the training pixels. For both cypress and tupelo the fractions were estimated to be approximately 0.90. An intelligent rule-based process then automatically solves Equation 2 for $T[n]$, using the training pixels for $R_m[n]$ and transforms the estimated mean fraction into $k_m[n]$. Then, $N_m[n]$ is treated as a second unknown. $N_m[n]$ is automatically solved using a process that is analogous to the $N_m[n]$ selection process described above for the classification module.

The process employed by the signature derivation module yields a signature, $T[n]$, that represents the material that was most common to the set of training pixels at the specified k_m. This is in contrast to most traditional multispectral classifiers that produce signatures that include the spectral variance represented by the pixels in the training set. Therefore, the subpixel process does not simply accommodate the spectral variance of the training set pixels in the signature. It instead extracts the signature of a material that is common to the training set pixels. This has the advantage of allowing relatively pure signatures for materials of interest to be derived from mixed pixels, rather than deriving signatures for the mixture of materials in the training set. Rather than using the variance of the training set pixels to define the variance of the signature, the process uses $T_m[n]$ extracted from pixels within the training set and away from the training set to derive the variance. This has the advantage of suppressing the variance introduced by the other materials in the training set. This produces signatures that perform relatively uniformly across the scene being processed, at least to the extent that the natural variance of $T[n]$ is represented by the training set.

After deriving the spectrum of the material of interest, $T[n]$, the signature derivation module next automatically derives a set of spectral tolerances that predict how much $T_m[n]$, defined by Equation 4, might vary from the nominal spectrum due both to actual spectral variations of $T[n]$ and to errors in selected $N_m[n]$ and $k_m[n]$ during classification. The tolerances are used during the classification process to filter the spectra of the detected occurrences of the material of interest, $T_m[n]$, thereby minimizing errors of omission and commission during classification.

2.3 Subpixel Processing in Relation to Other Approaches

The subpixel processing provides a more robust discrimination than traditional per pixel multispectral classifiers for pixels where the material of interest is mixed with other materials. It also provides more uniform performance away from the training area. This is a consequence of the enhanced purity of reference signatures, discussed above. It is also a consequence of the background suppression capability used during classification (Equation 4). The spectral contribution of the other (background) materials in the pixel can significantly distort the pixel spectrum from that of the material of interest. By suppressing these background contributions, discriminations can be maintained between spectrally similar materials even when the material of interest occupies only a small fraction of the pixel. Traditional multispectral classifiers are not able to directly suppress the background contributions. Instead, the variances imposed by the background materials are accommodated by the other classifiers. If too little variance is accommodated, then only the purest pixels can be discriminated. If two much variance is accommodated, then mixed pixels can be included in the classification but the discrimination sensitivity is correspondingly reduced. The traditional classifiers have successfully performed species level discriminations for large contiguous stands and fields. They have had mixed success, however, when the species were mixed with other terrain units.

The subpixel processing approach used for signature derivation and background suppression yields generally different discrimination performance characteristics than a Linear Mixing Model (LMM) (Adams et al, 1986). The LMM evaluates each pixel spectrum as a linear sum of a basic set of image end-member spectra. These typically include a "shade" spectrum and **n** other scene representative orthogonal spectra, where **n** is the number of sensor spectral bands. The end-member spectra include "background" end-members, such as bright soil, vegetation, water, and "residual" end-members, such as concrete, tarmac, and roofing material. The background end-members are assumed to be in every image pixel, and the residual end-members are assumed to be in only some of the pixels. The output is typically presented in the form of fraction planes for each end-member spectrum, which give the derived fractions of each end-member spectrum for each pixel. A residual plane is also produced which gives the root-mean-square-error of the fit for each image. The LMM has been most reliably used to classify pixels in a manner analogous to a principal components analysis. There have also been attempts to use the LMM for subpixel analysis by either substituting the material of interest spectrum for one of the residual end-member spectra, or by comparing the error spectrum to the material of interest spectrum. The LMM can produce reasonable subpixel results when the material of interest has a spectrum that is orthogonal to the other end-member spectra, and that is unique in the scene. The performance is not as reliable when the material of interest spectrum is either not orthogonal to the other end-member spectra or the spectrum is not unique in the scene. The LMM should, for example, do well classifying subpixel occurrences of tarmac or "scene vegetation," but it would not be appropriate for detecting subpixel occurrences of specific vegetative species.

The non-parametric subpixel processing also yields results different from those produced using fuzzy set classification logic (Wang, 1990ab; Jensen, 1995). Fuzzy classification also yields subpixel "membership grade" information (i.e. a pixel might have a fuzzy set membership grade value of 0.7 cypress, 0.2 tupelo, and 0.1 water). However, it arrives at the membership grade statistics using supervised fuzzy set maximum likelihood or fuzzy c-means clustering logic and the results are not the same as the subpixel processing described here. Both the LMM and the fuzzy set logic assume that the overall composition of each pixel is constrained to be some combination of the defined image classes (or end members for LMM). The AASAP process does not constrain the overall composition of the pixel in order not to introduce unwanted errors in material fraction estimates.

3. Application of Subpixel Processing to Discriminate Cypress and Tupelo Materials of Interest in Landsat Thematic Mapper Imagery

The subpixel processing logic was tested on forested wetland study areas in South Carolina and Georgia using Landsat Thematic Mapper data.

3.1 Remotely Sensed Data

Landsat TM imagery obtained on May 4, 1992 after complete spring leaf-out were used. Four study areas from within the Landsat TM scene were analyzed (**Figure** 3). Two 150 x 150 pixel areas were used for signature training and classification refinement. The two training areas were processed to detect the locations of individual cypress and tupelo trees. In addition, two 256 x 256 pixel test areas were also classified using the subpixel processor.

Low altitude color infrared (CIR) aerial photography were obtained at a nominal scale of 1:7,000 and 1:22,500 for the two training areas 14 and 15 days after the TM overpass. Large stands of cypress and tupelo, and in some cases individual tree crowns, could be identified in the 1:7,000 scale photographs. National Aerial Photography Program (NAPP) CIR aerial photographs (1:40,000 scale) were used to analyze regions of the study area outside the two training areas.

3.2 *In situ* Field Data Collection for Training and Error Assessment

In situ field sampling was conducted to:

1) identify relatively pure, homogenous stands of cypress and tupelo for signature training;

2) identify locations of cypress trees mixed with other tree species, and tupelo trees mixed with other tree species, for classification refinement, and

3) to measure errors of omission and commission in the accuracy assessment phase of the project.

Sampling was restricted to areas that were accessible by foot. However, due to an exceptionally dry field season (summer of 1993), many deep wetland areas that normally are inaccessible by foot were accessible. The location of TM pixels were found in the field using a TM pixel grid that was registered and overlaid on the 1:7,000 scale CIR photographs. A global positioning system (GPS) unit was used to identify ground control points for georeferencing and to acquire ground coordinates for training areas.

3.3 Application of Subpixel Processing to Extract Individual Specie Material of Interest (MOI) Information

The Landsat TM scene was ordered with nearest-neighbor resampling, 30 x 30 m pixels and path orientation. Nearest-neighbor resampling is preferred over cubic convolution or bilinear interpolation resampling methods for subpixel processing because it minimizes spectral degradation. Resampling for geometric correction is minimized with path oriented and 30 x 30 m pixel data. Preservation of the raw spectral relationships between pixels and band-to-band spectral relationships within a pixel increase the potential for subpixel spectral discrimination. Geometric correction of the imagery for cartographic and cosmetic purposes was performed with cubic convolution resampling after subpixel processing.

Georeferencing was required to associate the ground coordinates of training and accuracy assessment sites with the corresponding Landsat TM pixels. To avoid additional resampling of the TM imagery, the ground coordinates of these sites were plotted on a digitized base grid map. This map was geometrically registered to the TM image. To find the location of classified pixels in the field, another form of image registration was performed. The TM pixel grid was registered to the 1:7,000 scale CIR photographs and printed on transparencies for overlay on the photographs. The georeferenced TM image was not used for subpixel processing.

As previously discussed in Section 2, the subpixel processing involved using one set of training pixels to develop the cypress spectral signature and one set to develop the tupelo spectral signature. Another set of training pixels were used to refine the classification. All training pixels and the classification evaluation and refinement occurred in the two 150 x 150 training image areas. A signature can be developed for almost any material for which the analyst can identify a training set. The principal restrictions are a) the amount of material in the training pixels should exceed 20 percent of a pixel, and b) the material should have relatively unique and consistent spectral properties within the set of training pixels. The training set does not need to come from the same image being classified (Huguenin, 1994). After the spectral signatures were developed and refined, the remaining two test image areas were processed.

Known locations of relatively monospecific stands of cypress and relatively monospecific stands of tupelo trees were used as training pixels. Fifty-one TM pixels of cypress from one training area were used. Field verification revealed that each of these pixels contained approximately 85% cypress. Seventy-two pixels of tupelo from three different training areas were used as training pixels. These pixels contained approximately 90% tupelo. These training pixels were used by AASAP to create a spectral signature for each species. The processor then evaluated each pixel in the image to determine if the pixel contained a subpixel spectral component that resembled the species spectral signature within a specified range of tolerances (refer to the subpixel classification phase in Figure 2). A variety of tolerances (thresholds) were evaluated, in an iterative fashion, until an optimal set of results were achieved.

Classification refinement involved evaluating the classification output from each iteration of the thresholds. These intermediate classification results were evaluated with the 1:7,000 aerial photographs, some field checking, and the use of another set of training pixels. These training pixels were known to contain subpixel occurrences of the species. The classification results were refined until the maximum number of cypress containing pixels were correctly classified with the minimum number of incorrectly classified pixels.

4. Accuracy Assessment

An extensive accuracy assessment quantifying errors of commission and omission was performed for the cypress and tupelo subpixel processing classification results. Random sampling techniques were used to select 200 locations that were field verified for the occurrence of cypress trees and 200 locations that were field verified for the occurrence of tupelo trees. For both cypress and tupelo, 100 pixel locations were field verified to measure errors of commission (approximately 25 locations in each of the four image areas), and 100 pixel locations were field verified for errors of omission (approximately 25 locations in each of the four image areas).

To measure errors of commission for cypress, 100 of the pixels classified as containing cypress were selected using a random cluster sampling technique. Five pixels classified as containing cypress were randomly selected in each of the four image areas. The four nearest pixels to each randomly selected pixel, that were classified as containing cypress, were also selected. Random cluster sampling was employed to reduce the areas of field verification to localized clusters. Due to the inaccessibility of some deep wetland areas, some randomly selected pixels were replaced by other randomly selected pixels. This same method was used to measure errors of commission for tupelo.

Field verification involved orientation with the TM grid overlaid on the 1:7,000 scale CIR aerial photographs and the hand-held global positioning system. Due to a large abundance of natural ground reference features that were visible in the aerial photographs (for example, large tree crowns, canopy openings, and waterways), it was possible to identify the ground location of individual TM pixels with a high level of certainty. If one or more cypress trees occurred within the estimated ground location of the TM pixel, it was recorded as a correctly classified cypress pixel.

5. Results and Discussion

Subpixel classification results for tupelo wetland for one of the training areas are shown in **Figure 4.** The classified pixels are draped over a Landsat TM band 4 image in various colors ranging from yellow through orange to green that represent the proportion (fraction) of tupelo found within each pixel (refer to inset table in Figure 4). For example, there were 365 pixels within this subscene that contained >90% tupelo. Pixels with a high concentration of tupelo run throughout the center of the region in a well defined wetland area. **Figure 5** depicts both tupelo and cypress subpixel classification results overlaid on a TM band 1 image of the same training area. Pixels that contained any amount of tupelo are yellow, those pixels that contained any amount of cypress are blue, and those that contained any amount of both tupelo and cypress are red. The well defined wetland channel observed in Figure 4 is also apparent in **Figure 5** with dense concentrations of both tupelo and cypress. There are, however, sections of the deep wetland, for example along the edges, where it is primarily tupelo. In the central portion of the image, there are dense concentrations of cypress (blue).

The error evaluation revealed that 95 of the 100 selected pixels classified as cypress contained cypress, and 93 of the 100 selected pixels classified as tupelo contained tupelo. Cypress had a ~~[illegible]~~% 5 error of commission, and tupelo had a 7% error of commission (Table 2). To evaluate errors of omission, 10 stands of cypress and 10 stands of tupelo in each of the four study areas were identified using the CIR photography and field verification. Five of these stands in each study area were randomly selected and five pixels within these selected stands were selected using stratified random sampling. For cypress, 82 of the 100 pixels (25 from each image area) known to contain cypress, were successfully classified as cypress. For tupelo, 89 of the 100 known tupelo pixels were classified as tupelo. Table 2 lists the total accuracy for cypress, 89% (177/200), and tupelo, 91% (182/200). A Kappa coefficient of agreement (Congalton et al, 1991) is not applicable in subpixel classification because: 1) typically not every pixel in the image is classified (often only several materials are classified); and 2) a single pixel can be correctly classified as containing more than one material.

A Kappa coefficient of agreement (Congalton et al., 1991) is not applicable in subpixel classification because unlike traditional land cover classification, each pixel in the image is not assigned to one of the different land cover classes. In subpixel classification there is often only one or a few materials of interest (for example land cover types or objects of interest such as bridges) classified. For each material of interest, each pixel in the image is classified into one of ten percentage classes according to the amount of material of interest present in the pixel. Typically, many pixels in the image are classified as containing no amount of the material of interest and therefore cannot be accounted for in an error matrix. Additionally, a single pixel can be correctly classified as containing more than one material of interest, which is a condition not suitable for current accuracy assessment techniques.

Table 2. Accuracy Assessment Results for the Classification of Cypress and Tupelo Using Subpixel Processing.

Class	Commission Accuracy	Omission Accuracy	Total Species Accuracy
Cypress	95/100	82/100	89%
Tupelo	93/100	89/100	91%

Of the 182 pixels correctly classified as tupelo, all 182 sites contained tupelo trees mixed with other tree species. At most of these sites the pixel area was predominantly occupied by tupelo (greater than 50%), but at many sites tupelo trees occupied less than 50% of the pixel area. In approximately a dozen of these sites, only a few tupelo trees occurred representing as little as 20% of a pixel area. In evaluating the accuracy of tupelo in each of the four study areas, it was observed that the accuracy in each area was not significantly different. The accuracy in one training area was slightly better than the other three areas, but no area had a total accuracy lower than 84%.

Based on this sample, it can be stated with 95% confidence, that 93% ± 1.2% of all pixels classified as tupelo are correct. Eighty-nine percent, plus or minus 1.2%, of all areas containing tupelo were correctly classified. For cypress, also at the 95% confidence level, 91% ± 1.2% of all pixels classified as cypress are correct. Eighty-seven percent, ± 1.3%, of all areas containing cypress were correctly classified.

A follow-up study comparing the subpixel classification of cypress and tupelo versus a maximum likelihood and minimum distance classification of cypress and tupelo will be reported in a separate paper.

6. Conclusions

Spectral subpixel processing classified tupelo at 91% accuracy and cypress at 89% accuracy in Georgia and South Carolina wetlands. Extensive field investigation revealed that both tupelo and cypress trees were successfully classified when they occurred both as pure stands and as mixed stands, i.e. with other tree species. Relatively pure stands of tupelo and cypress trees were detected in high concentrations in the deep wetland areas. Less dense concentrations of tupelo and cypress were classified in the broad wetland transition zones where tupelo and cypress were typically mixed with other tree species. Small, isolated pocket wetlands containing small numbers of tupelo and cypress trees were also classified.

The subpixel process can be used to detect spectrally unique materials in any multispectral data source. The process addresses the mixed pixel problem and enables the classification of materials smaller than the spatial resolution of the sensor by: 1) extracting a pure subpixel signature of the material of interest (units of the pixel that are not the material of interest are removed from the signature), and 2) extracting and analyzing subpixel components of each pixel in an image and identifying those subpixel components that match the material of interest spectral signature. While the analyst could use a library of pre-existing spectral signatures such as that collected by NASA, the algorithm presented here provides the analyst with an automatic signature development capability that produces signatures tailored to a specific material of interest in the study area with its unique environmental conditions.

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8. Figure Captions

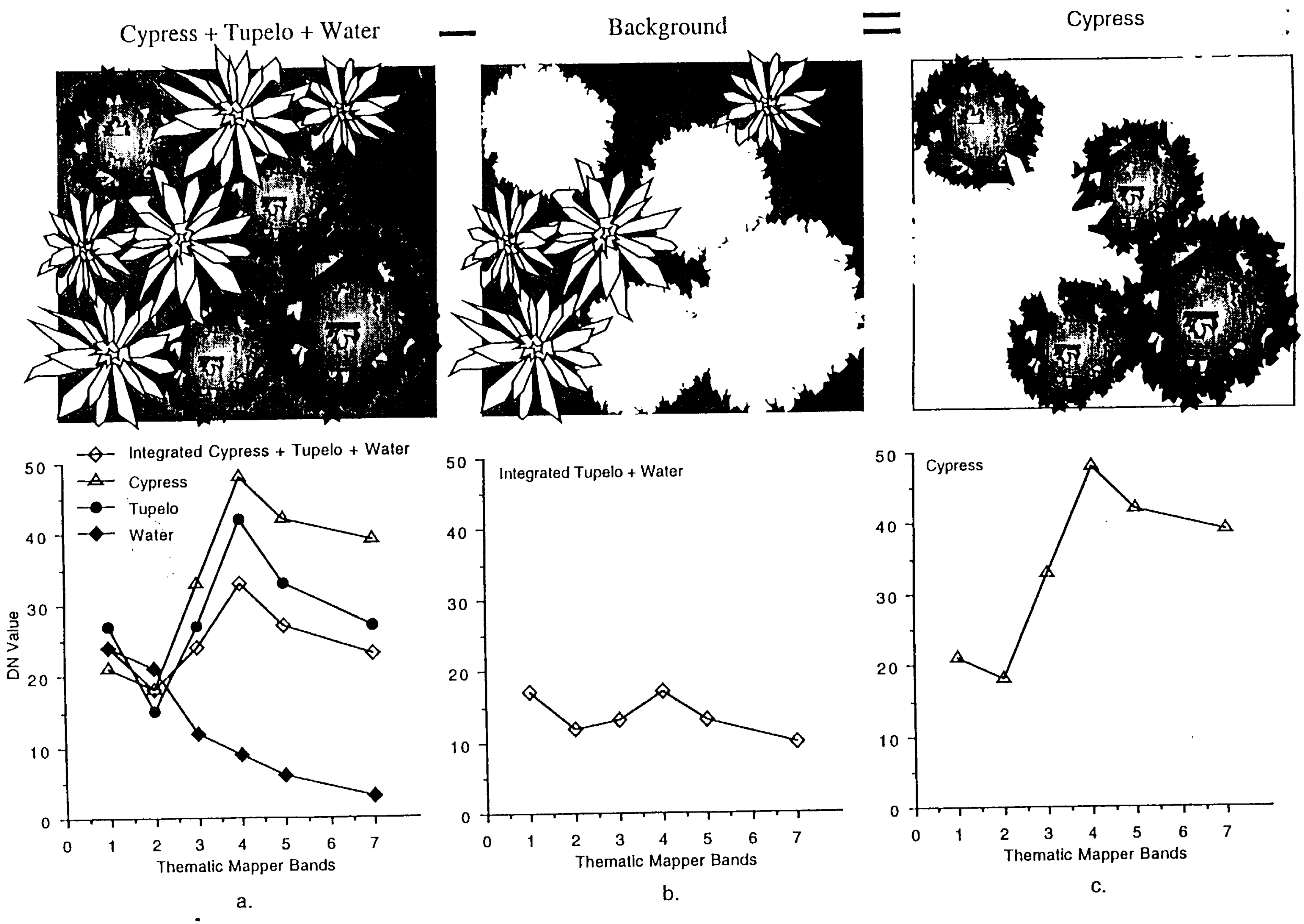
Figure 1. A schematic diagram of how a material of interest (MOI) (cypress in this example) is extracted using subpixel processing from a hypothetical Landsat TM 30 x 30 m mixed pixel containing equal proportions of cypress, tupelo, and water. (a) The integrated spectrum for the pixel bears little resemblance to the pure spectrum of any of its constituents. (b) The background reflectance spectrum is identified. (c) The background reflectance spectrum is subtracted from the original integrated spectrum leaving only information about the proportion of the material of interest, cypress, within the pixel.

Figure 2. Typical stages in subpixel processing.

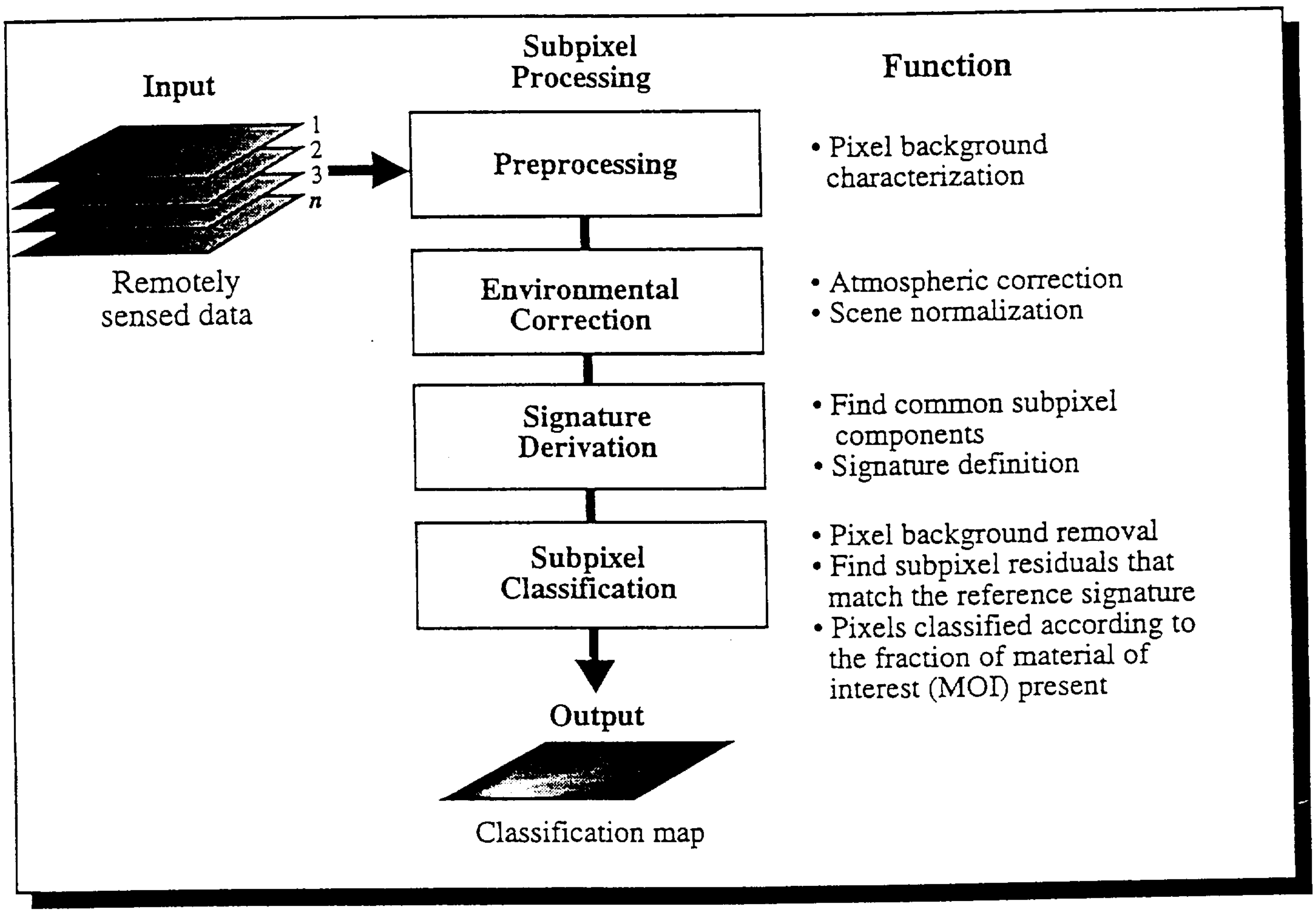
Figure 3. Approximate location of training and test study areas in South Carolina and Georgia.

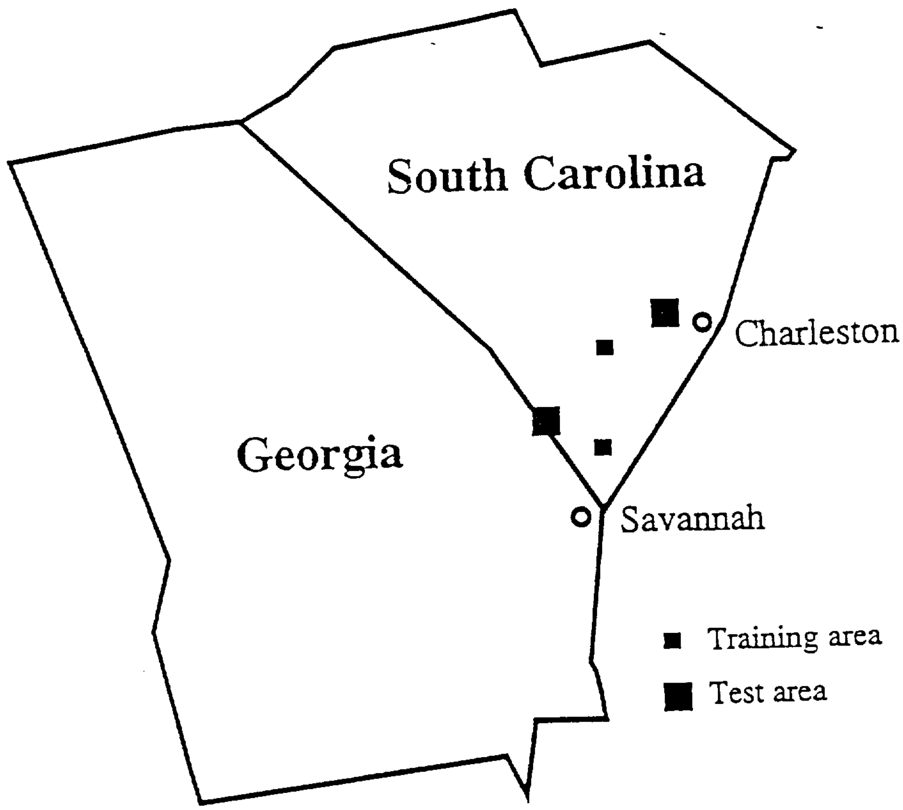
Figure 4. Tupelo land cover derived from subpixel processing of Landsat TM data for a region in South Carolina. Valuable information about the proportion of tupelo found within each pixel is summarized in the inset table and color coded.

Figure 5. Land cover derived from subpixel processing of Landsat TM data for a region in South Carolina. Pixels containing any amount of tupelo are in yellow, any amount of cypress are in blue, and pixels containing any amount of both cypress and tupelo are in red.


Cypress + Tupelo + Water
Background
Cypress
Integrated Cypress + Tupelo + Water
Cypress
Tupelo
Water
DN Value
50
40
30
20
10
0
0 1 2 3 4 5 6 7
Thematic Mapper Bands
a.
Integrated Tupelo + Water
Thematic Mapper Bands
b.
Cypress
Thematic Mapper Bands
c.

1


Input
Subpixel Processing
Function
1
2
3
n
Remotely sensed data
Preprocessing
• Pixel background characterization
Environmental Correction
• Atmospheric correction
• Scene normalization
Signature Derivation
• Find common subpixel components
• Signature definition
Subpixel Classification
• Pixel background removal
• Find subpixel residuals that match the reference signature
• Pixels classified according to the fraction of material of interest (MOI) present
Output
Classification map


South Carolina
Charleston
Georgia
Savannah
Training area
Test area